CALIFORNIA ENVIRONMENTAL PROTECTION AGENCY
AIR RESOURCES BOARD

TECHNICAL SUPPORT DOCUMENT FOR
STAFF PROPOSAL REGARDING REDUCTION OF GREENHOUSE
GAS EMISSIONS FROM MOTOR VEHICLES

OTHER CONSIDERATIONS

August 6, 2004

OTHER CONSIDERATIONS

This technical support document describes the consumer response modeling effort and provides more information on manufacturer response. Consumer response was estimated using CARBITS model. The technical document for the model is attached as an Appendix.

The impact analysis presented in the ISOR show the potential changes that may occur as compared to a predicted baseline. That is, first a baseline forecast of the economy, vehicle attributes, or other characteristics are predicted using the data and information from the historical data and trends. Then, the potential changes that the proposed regulation may cause are estimated using models and analyses. The difference between the two show the potential impact the regulation may have.

1.0 Consumer Response Effects on Emissions and State Economy

The ARB's climate change regulation may lead to an increase in new vehicle prices, starting with model year 2009. In addition to an increase in price, however, it is expected that many of the technologies that manufacturers employ to lower greenhouse gas emissions to comply with the regulation will, as an outgrowth, result in vehicles with lower operating costs than comparable pre-regulation vehicles. These changes in vehicle attributes may affect consumer purchase decisions. For example, not all consumers would be willing to pay more for the vehicle that they would have purchased. Some may purchase a different vehicle commensurate with their budget. Others may wait until the following year, or respond in some other way. Still other consumers may highly value the reduction in operating cost, in which case the vehicle would be more attractive. Such decision changes, referred to as consumer response, can affect the California vehicle fleet mix and possibly emissions.

1.1 Background

A model, known as CARBITS, was used to estimate consumer response (i.e., the estimated change in the type and number of vehicles sold) to changes in vehicle attributes. The model is fully explained later in this Technical Support Document. The attribute changes considered are the vehicle price increase necessary to cover the estimated compliance costs of the climate change regulation, and a reduction in vehicle operating costs which is an outgrowth of the technology employed to reduce greenhouse gas emissions.

The Appendix to this technical support document explains the development of the model, its details, and how the baseline inputs were used to run the model.

The CARBITS model is a consumer choice model and was developed by the Institute of Transportation Studies at the University of California, Davis. The ultimate objective of the modeling effort is to investigate the potential fleet mix changes and any criteria pollutant impact that may result as a side effect of the climate change regulation. The results show that even if consumer response is taken into account, the staff proposal would have a negligible effect on tailpipe criteria pollutant emissions.

Consumer response may manifest itself in different ways. The consumer response to the regulations is defined as the difference in the California fleet mix between the forecasted baseline and the regulation scenarios. The baseline scenario is a depiction of the passenger vehicle fleet in the absence of the climate change regulation.

While vehicle prices may go up with respect to the regulatory scenarios, the operating costs are expected to be lower. As a consequence of the price increase, consumers may respond by purchasing fewer new vehicles and holding on to their current vehicles a bit longer. This shift in vehicle holdings may lead to aging of the vehicle fleet. The aging of the fleet could result in higher polluting cars staying in service longer than they would have remained otherwise. This delay in fleet turnover could cancel out some of the progress that California is making in reducing criteria pollutant emissions from mobile sources. On the other hand, the reduction in operating cost may make vehicles more attractive, thus offsetting any losses in sales. The purpose of the CARBITS model is to quantitatively investigate the possible magnitude and direction of such changes.

1.2 Baseline Predictions

The baseline predictions to estimate consumer response consists of forecasts of vehicle prices, operating cost, and vehicle performance. All other vehicle attributes were kept unchanged. The figures 2.1 through 2.6 of the Appendix to this document show the graphic depiction of the baseline scenario.

All vehicle prices were predicted to rise slightly from 2003 to 2009. The price increases were the result of technological improvements for other vehicle attributes and consistent with the technology cost estimates presented in the ISOR.

Fuel consumption was predicted using the Martec data that estimated it for model year 2009. A linear extrapolation between 2002 and 2009 determined the operating costs for the years between the end points. The predicted baseline fuel consumption declines slightly between 2010 and 2013 as a result of smoothing of the trend towards flattening of the trend for after 2009 model year.

Vehicle performance, as measured by the time a vehicle takes to go from zero to 30 miles per hours (Z30), improves somewhat until 2009 and then flattens afterwards. Traditionally, performance is reported using the time it takes to speed up to 60 miles per hour. However, the CARBITS model was developed from data that only had Z30 data. The ISOR as well as this document contain the tables that describe the baseline scenario.

1.3 The Regulatory Scenario

Using the cost estimates from the ISOR, staff developed a regulatory scenario to use as inputs to CARBITS in an effort to estimate consumer response to changes in price and operating costs. The ISOR contains the tables that describe the regulatory scenario. The scenario consists of, the estimated average price increase needed to cover manufacturer compliance cost estimated in Chapter 6 of the ISOR, and the operating cost reductions.

The price changes are distributed among 14 CARBITS classes, and calculated for the near-term phase (2009-2012) of the regulation as well as the mid-term (2013-2016) phase. A combination of near and mid-term price changes were calculated for some years based on the assumption that the regulation will be phased in over a period of years.

The technology costs were estimated for 5 vehicle classes. However, CARBITS uses 14 vehicle classes. To translate the costs from 5 to 14 classes, staff assumed that vehicles of similar size will have the same price and operating cost changes. For example, CARBITS mini, sub-compact, and compact cars fit in the same class as the small car category used to estimate technology costs, and therefore see the same price change. Similarly, staff assumes that operating costs would decrease by the same percentage for the mini, sub-compact, and compact cars.

The technology assessment also included estimates of operating cost reductions. The reductions were translated to the 14 CARBITS classes. Because the regulation is phased in over several years, the operating cost reductions account for the portion of the fleet that would become compliant with the proposed regulation in each year.

Consumer response was estimated by comparing the baseline with the regulatory scenario. The CARBITS model estimated the results for both scenarios. The details of the model are in the Appendix and the reader is referred to the Appendix for the rest of the discussion on consumer response.

The next section provides information on how the automobile manufacturers are likely to respond to cost changes. Some of the insight learned from the literature is included in the section.

2.0 Manufacturer Response

The economic impact analysis of the climate change regulation presented in the ISOR provides conservative estimates. The results are conservative in that the analysis assumes that the compliance costs of the regulation will not change over time. It further assumes that the costs will be passed on to consumers in their entirety beginning the first year and continue on with no additional change due to innovation, and no distribution of costs to different vehicle classes or non-price methods of recovering costs.

Staff adopted this approach because there is insufficient quantitative information available to justify other assumptions. Nevertheless, there is ample evidence that automobile marketers use a variety of price and non-price tools in an effort to optimize sales. The purpose of this section is to provide a qualitative assessment of the options that are available to automobile manufacturers, and that they have used historically, to maintain sales while simultaneously complying with various regulatory requirements.

Staff reviewed consultant reports from ITS and the literature to assess the information available on these points. Staff believes, based on its review, that the increases in vehicle prices due to the regulation could well be less than the estimates provided in the staff analysis. Staff's main findings with respect to strategies that automobile manufacturers may employ to comply with regulatory requirements are presented.

To comply with the climate change regulation, automobile manufacturers have a number of options. The option that they choose will depend on costs, market conditions, and consumer preferences. Whichever way they choose to respond, it is likely that the automobile manufacturers will devise alternatives to soften the impact of compliance costs on prices. They can use marketing tools and technology-based cost decreases over time to bring down the compliance costs to a fraction of what the consumer response analysis assumed. Manufacturers have complied in the past with regulations that increase vehicle production cost. Review of such cases helps to shed light on manufacture response. This section provides findings from a review of regulatory compliance costs in the automobile market over the past three decades.

The climate change regulations address automotive emissions. We therefore reviewed past compliance costs associated with automobile emission control regulations. Because the industry response to other regulatory regimes may shed light on general trends, we also reviewed the response of automobile manufacturers and their customers to two other disparate cases of increased cost: the regulation of automotive safety and fuel consumption. We found that when put in a historical perspective, the economic impact analysis outlined in the

ISOR can be characterized as a conservative scenario. Specifically, our historical review found that:

- Average, per-vehicle compliance costs are considerably higher in the initial years of regulatory implementation than in subsequent years. The cost of compliance tends to decline with passing years, due to the influence of economies of scale, learning curve effects and technological innovation. The cost of airbag systems, for example, dropped by 75 percent over the first 15 years of compliance.

- Auto manufacturers do not typically pass along 100 percent of increased compliance costs as higher retail prices in the first year of compliance. One conservative analyst estimates that automobile manufacturers absorb 100 percent of compliance cost increases in the first year then pass along roughly two thirds of that cost in the following year, and the balance in later years.

- Automobile manufacturers do not recover the same proportion of compliance cost increases across all product lines. Instead, the relevant price increases focus on the vehicle classes and customers seen as least sensitive to such changes. Typically, higher price increases for popular and high-end models cross-subsidize lower price increases to "economy-class" models.

- Automobile manufacturers use methods other than price increases to recoup compliance cost increases, including changes in "standard" vehicle content and adjustments to incentive packaging and financing terms.

- If consumers regard compliance-related improvements as valuable, new vehicle sales may increase, despite increased prices. In the European Union, sales of new lower-emitting diesel vehicles have doubled despite an average price $1567 higher than comparable gasoline-fueled vehicles.

2.1 Compliance Cost Reduction Factors

Average, per-vehicle compliance costs are considerably higher in the initial years of regulatory implementation than in subsequent years. Among the factors contributing to the reduction of compliance costs after initial implementation are: economies of scale, learning curve effects and technological innovation.

Economies of scale are achieved when automobile manufacturers produce greater quantities of compliant vehicles or when automobile suppliers produce larger quantities of compliance-related components. For example, a 1988 U.S. DOT study determined that the cost of a driver-side airbag for a Ford Tempo was $1233 at a production volume of 25,000, and $391 for a production run of 350,000. To the extent that related equipment is produced in larger quantities, compliance costs will be lower.

Insofar as other states or countries choose to meet California's climate change emission standards, for example, greater compliance cost reductions may be achieved through economies of scale. Similarly, to the extent that automobile manufacturer demand for compliance-related equipment can be consolidated by suppliers, greater economies of scale will be achieved. The rate at which AB1493 compliance technologies penetrate the product lines of automobile manufacturers will also affect economies of scale. For example, if an automobile manufacturer phases the same compliance component into its entire product line in 5 years, it can achieve greater economies of scale more quickly than if it takes 10 years to phase in the same component.

As automobile manufacturers and suppliers gain experience in installing or producing a particular piece of compliance-related equipment, they learn to do so more efficiently. This increased productivity – or learning curve effect -- is achieved through cumulative production experience. Like economies of scale, the automobile industry's learning curve contributes to lower compliance costs over time.

The automotive design (or re-design) process permits car makers to better integrate compliance equipment with the balance of the vehicle. Because the automotive design cycle has been dramatically shortened over the past two decades, the learning curve benefits of design integration should be accelerated.

Once new regulations are established, automobile manufacturers focus on learning how to comply with them at the lowest possible cost. Technological innovations substantially reduce compliance costs as research and development resources are mobilized to identify new, less costly methods of meeting standards. The development of microchip-based crash sensors, for example, permitted automobile manufacturers to install airbag systems using only one frontal crash sensor rather than four or five. Other cost saving innovations included the development of more cost-effective airbag inflators, and replacement of steel with reinforced plastic in airbag housings.

At other times, innovations may permit automobile manufacturers to reduce compliance costs by avoiding compliance altogether. The development of minivans and sport utility vehicles, for example, exploited a loophole in Federal CAFÉ regulations, which, initially, allowed light trucks to avoid meeting fuel economy standards.

All three of these factors – economies of scale, learning curve effects, and technological innovation – helped automobile manufacturers reduce compliance costs for safety, emissions and fuel consumption standards. We can reasonably expect them to reduce the cost of complying with AB 1493 climate change emission standards with every passing year.

2.2 Market Share and Cost Recovery

Automobile manufacturers do not typically pass along 100 percent of increased compliance costs as higher retail prices in the first year of compliance. Automobile manufacturers will seek to recover a portion of compliance cost increases through price increases. But, intense competition and pressure to retain market share motivate automobile manufacturers to apply price increases selectively, raising prices only where and when consumers are most inclined to accept them.

For example, if automobile manufacturers incur substantial additional compliance costs in the same year that automobile loan interest rates increase sharply, they may choose to absorb a portion of those costs for fear that price increases, on top of monthly payment increases caused by higher rates, might impact sales.

Analysis of historical compliance data indicates that automobile manufacturers have flexibility in determining when to pass along increased compliance costs in the form of new-car price increases. In some years, average new car prices were actually reduced while average compliance costs increased.

A Brookings Institute study of automobile manufacturer recovery of emission compliance cost increases found that automobile manufacturers generally absorbed 100 percent of additional compliance costs in the first year, and then passed on approximately two thirds of the increase in the following year. Depending on how quickly the cost of complying with a given standard is reduced by the factors discussed above, a two-thirds cost pass-through in the second year could eventually recover more than 100 percent of related costs.

The imperative to retain market share is largely driven by automobile manufacturers' need to support substantial fixed costs in the form of long-term labor agreements. Because of these agreements, reductions in production volume are not always accompanied by commensurate reductions in costs. Idled workers must still be paid. It is therefore in the interest of automobile manufacturers to price their product with an eye to maintaining full employment of its productive resources.

2.3 Pricing Across Product Lines

Automobile manufacturers do not recover the same proportion of compliance cost increases across all product lines.

Even with standardized compliance equipment, the per-vehicle cost of compliance can be expected to vary somewhat by make and model. But variations in the actual per-vehicle cost of compliance are only part of the reason that automobile manufacturers try to recover different proportions of production cost increases from different product lines.

Some customers are more sensitive to price increases than others. Automobile manufacturers are aware that the sales impact of price hikes varies from one market segment (and one model) to another. So when it comes to recovering increased compliance costs through pricing, automobile manufacturers do not target the same level of recovery from every product line. In the same way that automobile manufacturers apply buyer incentives such as rebates selectively, so price increases are applied selectively to the product lines that can absorb them with the least impact on profit. Analysis of historical price and sales data confirms that the impact of increased prices on sales does vary from one class of vehicle to another.

Review of historical compliance episodes also shows that automobile manufacturers use differential price increases to effectively cross-subsidize the compliance costs of one group of vehicles with the increased profits from another. Our case study of federal passive restraint regulations, for example, shows that as driver-side airbags were added to economy class vehicles, average prices increased by $7 more per vehicle. But as airbags were added to mid-priced cars, the average per-vehicle price increase was $474 higher.

To accurately project the automobile price changes attributable to the cost of compliance with climate change regulations, it is necessary to take such variations into account. It would be unrealistic to assume that automobile manufacturers seek the same level of cost recovery across all product lines.

2.4 Alternate Ways of Cost Recovery

Automobile manufacturers use methods other than price increases to recoup compliance cost increases.

Automobile manufacturers that experience production cost increases as a result of new compliance requirements do not necessarily resort to new-car price increases to recover increased costs. The price sensitivity of new-car buyers, (“sticker shock”), is well known to automobile manufacturers, who can recover cost increases in ways that are less visible to consumers and therefore, less likely to impact purchase decisions.

A substantial portion of automobile manufacturers’ profits are generated by financial services subsidiaries catering to new car buyers and dealers. Adjustments in the credit terms or the duration of a new-car loan can add hundreds of dollars to an automotive finance corporation’s bottom line. For example, shifting the duration of a $23,000 automobile loan from 48 to 60 months increases the amount of interest paid by $600 over the life of the loan. Increasing the interest rate of the same 60-month loan by one point (from 5% to 6%) adds another $600 to the amount of interest paid by the borrower.

Automobile manufacturers now apply sophisticated revenue management systems to adjust incentive plans for maximum profitability. Computerized models help automobile manufacturers determine how to adjust incentive packages on specific models in selected regions to minimize the negative impact on sales and profit. Incentive programs offered to dealers are managed with similar tools. It is common for the level of incentives offered on specific vehicles to change by thousands of dollars from month-to-month, while the MSRP for the same vehicles remains unchanged.

Automobile manufacturers also manage revenue from each product line by changing the features and equipment included in "standard" vehicle sales packages, without making corresponding changes in price. Such changes, known as "de-contenting", can be accomplished from one year to the next. In 2003, for example, General Motors eliminated ABS as standard equipment from most of its models. The ABS braking system cost GM approximately $160 per vehicle, while new car buyers pay an average of $470 for the safety feature. The opposite strategy is also employed. Manufacturers sometimes add hundreds of dollars of formerly optional equipment to the "standard" vehicle sales package while holding price constant.

In addition, automobile manufacturer research and development teams and their suppliers are constantly developing lower-cost materials and devices to replace existing parts. For example, chrome-plated steel bumpers were replaced with lower-cost composite bumpers. Swapping in lower-cost vehicle content without corresponding price reductions is another method of recovering unrelated cost increases. Revision of the terms of warranty programs, or the pricing of after-market repair and replacement parts are also cost-recovery opportunities.

These more subtle approaches to cost recovery permit automobile manufacturers to recoup compliance costs without incurring the same revenue penalty as comparable changes to MSRP. Unlike price changes, the net impact of these adjustments on the consumer's cost to own and operate a new vehicle is difficult to determine.

Given the prevalence of these revenue management techniques, it is reasonable to assume that a substantial portion of compliance costs will be recovered through non-pricing methods.

2.5 Consumer Sensitivity to Quality and The Environment

If consumers perceive sufficient value in compliance-related improvements, sales of compliant vehicles may increase in spite of higher prices. The standard economic relationship between increasing prices and declining sales applies only where product quality and other market conditions remain constant. Yet few studies of consumers' sensitivity to new-vehicle price increases have taken variations in vehicle quality into account.

If customers perceive that a compliance-related change in price is accompanied by a commensurate (or even greater), improvement in vehicle quality, sales may be unaffected, or increase, despite higher prices.

In Western Europe, compliance with self-imposed climate change emission standards has resulted in both higher new vehicle prices and increased sales of new low-emission diesel vehicles.

Because they value the reduced fuel consumption and lower climate-change emissions of the new diesel vehicles, European consumers have purchased more diesel vehicles, at a higher unit price. Despite an average price difference of $1567, diesel vehicles in the European Union have nearly doubled their share of new vehicle sales between 1992 and 2002, from 23 to 41 percent.

2.6 Other Findings

Other historical review findings contribute to our understanding of the overall impact of compliance costs on prices, consumers, and on the state's economy.

- Automotive technologies developed for compliance purposes sometimes yield unanticipated ancillary benefits in the form of improved vehicle performance -- in addition to reduced operating costs.

- Compliance-related price increases account for a comparatively small proportion of overall price increases. On average, compliance-related price increases account for less than 20 percent of new car price increases.

- New car sales depend on many factors other than new car prices, including the rate of national economic growth, household income, unemployment, consumer confidence and financing terms for new car loans. The impact of new car price increases on new car sales can be exaggerated or diminished by any of these factors, which are beyond the control of both the automotive industry and its regulators.

- Although average new car prices have increased over the past 30 years, automobile sales have also increased, because, on average, quality has improved and automobiles have become more affordable to own and operate.

- Prior to the adoption of new automobile regulations, industry representatives typically over-estimate per-vehicle compliance costs while arguing that compliance costs are excessive.

- Automobile manufacturers typically deny the value of regulatorily-imposed equipment changes while standards are still in development. However, if consumers perceive value in those improvements, automobile manufacturers do not hesitate to promote them in order to increase sales.

- Regulation of automobiles has created substantial new wealth in the form of jobs, income, market capitalization and tax revenues. In the past decade, for example, automotive airbag manufacturers have created approximately 90,000 new jobs, generated $60 billion in revenues and $5 billion in profits; about half of this growth has occurred in the United States.

These findings on the options available to manufacturers to comply with regulations help put the economic impact analysis into perspective. In short, the estimated impacts would likely be on the high side and furthermore do not consider the ongoing reductions due to further improvements.

In addition, the state and federal governments are undertaking a variety of initiatives to encourage a transition to low greenhouse gas transportation options. Such initiatives include the California Fuel Cell Partnership, the California Stationary Fuel Cell Collaborative, and the California Hydrogen Highway Network. Such initiatives could help accelerate progress in a variety of areas beyond that assumed in this analysis.

Appendix to

Technical Support Document: Other Considerations

California Air Resources Board – Institute of Transportation Studies (CARBITS) Vehicle Market Microsimulation Model for California

Documentation

David S. Bunch
Graduate School of Management, and
Institute of Transportation Studies
University of California, Davis

1. Introduction

CARBITS is a microsimulation forecasting model for the light-duty vehicle (LDV) market in the State of California, developed at the Institute of Transportation Studies (ITS) at University of California, Davis. The goal of CARBITS is to support policy analysis at the California Air Resources Board (CARB) related to California's AB 1493 legislation on greenhouse gas emissions[1].

The original research that provided the starting point for CARBITS was performed by a University of California multi-campus team of researchers (ITS-Davis and ITS-Irvine) during the period 1990-1997 through a series of projects sponsored at various points in time by the California Energy Commission (CEC), Southern California Edison (SCE), and Pacific Gas and Electric (PG&E), as well as occasional funding of students by the UC Transportation Center (UCTC). The impetus for the original research program was the need for an improved understanding of potential future market responses to the introduction of alternative fuel vehicles (e.g., battery-powered electric vehicles).

CARBITS integrates market response and demographic sub-models to produce dynamic, multi-year forecasts for the period 2000-2020. Forecasts are based on simulation of household behavior in the personal vehicle market, which comprises the vast majority of the light-duty vehicle market in California. CARBITS simulates vehicle transactions at the household level on an annual basis, and reports aggregated results for the range of years specified by the user (up through 2020). It should be noted that literally providing accurate "forecasts" of the future is not the primary purpose of CARBITS. Rather, it is intended to be as a policy analysis tool to help evaluate alternative regulation scenarios versus a "base case" or "status quo" scenario.

The basic structure of CARBITS is shown in Figure 1. The user establishes a specific forecasting scenario by providing input data of two types: a vehicle market scenario, and a fuel scenario. CARBITS uses a household-level behavioral model to simulate vehicle transaction decisions, including: (1) keep the current vehicles (no transaction), (3) replace an existing vehicle, or (3) add another vehicle to the household fleet. The behavioral model is an econometric-style model that has been estimated using survey data on actual household transactions, as well as responses to choice experiments containing hypothetical vehicle transactions. CARBITS also takes into account effects due to dynamic changes in demographics at the individual household level (including vehicle movements associated with some demographic changes, e.g., divorce or adult children leaving the household). Results are obtained by aggregating the individual household vehicle holdings to represent the California market. A more

[1] The acronym CARBITS, denoting the collaboration of CARB-plus-ITS researchers, was suggested by Fereidun Feizollahi in an early planning meeting for the development project.

detailed discussion of the behavioral model and related issues are included in the Appendix.

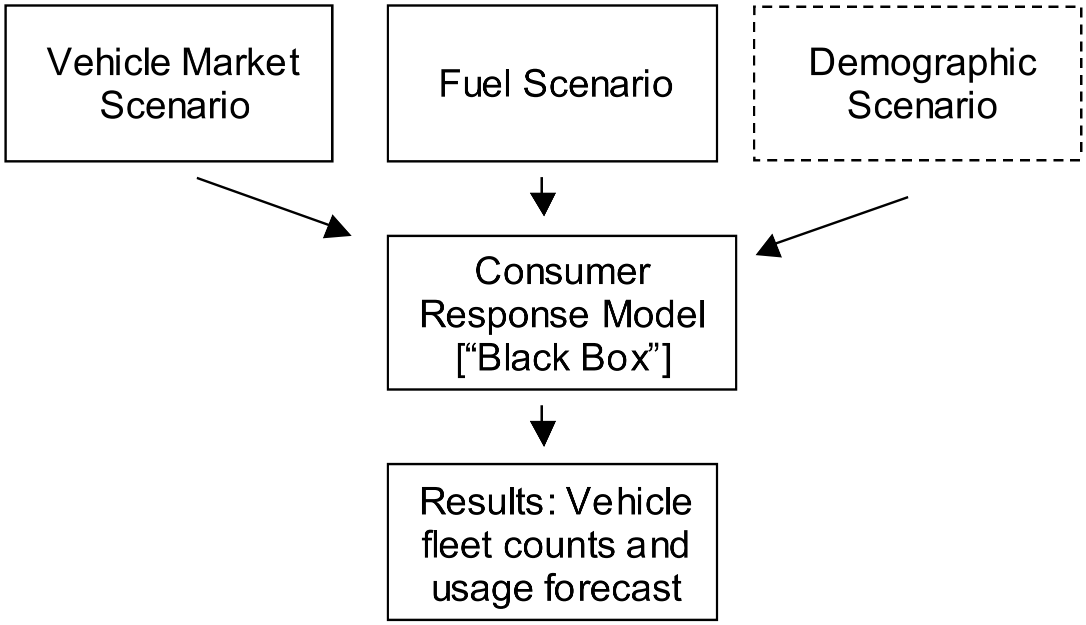


Figure 1. Overview of CARBITS

The vehicle transaction behavior model was developed in accordance with discrete choice theory, in which consumers (with varying characteristics) are assumed to make choices so as to maximize the "utility" they derive from various types of vehicles and vehicle features ("attributes"). This requires that all vehicles (vehicles available for purchase, and also currently held vehicles) be characterized by an appropriate set of variables associated with consumer preferences for competing *vehicle types* (e.g., a 1994 gasoline-powered subcompact car), as well as *vehicle attributes* (e.g., market value/purchase price, performance) associated with each type. CARBITS addresses behavior in both the used vehicle market as well as the new vehicle market, and therefore requires historical data on existing vehicles as well as "forecasts" of future vehicle types and their attributes. Purchase decisions by households are also influenced by, e.g., fuel operating costs, which are dependent on fuel prices, thus requiring a set of assumptions on future fuel prices. Details on inputs and outputs are given in sections 2 and 3, respectively.

With regard to implementation, the model uses a single executable program file (e.g., "carbits.exe") in conjunction with input files and databases; the program and files are compatible with Microsoft Windows-based computers. It is designed to run in "batch mode" using a traditional approach with ASCII input and output files. Specifically, files typically use comma-delimited (CSV) formats that allow the user to easily maintain a database of input and output data stored in Excel Workbook files.

The purpose of this documentation is to provide basic background on the CARBITS model, the methodologies used, and input and output specifications. More detailed examples of, e.g., alternative regulation-based input scenarios and how these results compare to the baseline scenario are beyond the scope of this document, and are to be found elsewhere in the CARB "Technical Support Document."

2 CARBITS Inputs

As described in the introduction, the CARBITS vehicle transaction choice model assumes that households make decisions based on vehicle market characteristics in terms of vehicle types and vehicle attributes. There are many different ways to define and characterize vehicle markets, and a complete discussion is beyond the scope of this document. The prototype version of CARBITS was an updated implementation of a model originally developed by ITS for Southern California Edison (SCE). Subsequently, CARBITS development involved multiple iterations and modifications, and it is likely that CARBITS will continue to be updated and enhanced.

2.1 Input File Specifications

The current version of CARBITS uses a vehicle market definition framework based on 14 *body-type-and-size* (BTS) classes—see Table 2.1.[2]. The current version of CARBITS is restricted to gasoline-powered vehicles, although future development could support an expansion to include other fuel technology types. A *vehicle type* is defined by a BTS class for a given model year and is characterized by 9 *vehicle attributes*—see Table 2.2[3].

A *Vehicle Market Scenario* file contains vehicle attributes for the years 1976-2020. CARBITS uses a fixed format (comma delimited) file with 631 rows: 1 header row, and one row for each of the 630 = 14 (BTS) x 45 (model years) vehicle types. The rows for model years 1976-2003 are based on historical attribute data, and generally would not be changed from the base case values. For an example of the first few rows, see Table 2.3.

CARBITS also requires a Fuel Scenario file containing gasoline prices for the period 2001-2020. Households make vehicle transaction choices based on a vehicle's fuel operating cost (in cents per mile), which is calculated from the fuel economy (miles per gallon) and the fuel cost (dollars per gallon).

[2] This framework was used in the original SCE model, and is similar to classification schemes used by the EPA and earlier versions of the California Energy Commission's CALCARS model.
[3] An additional attribute column, market availability, is added for convenience to allow for scenarios where certain vehicle types do not appear in the market.

Figure 1 indicates that the third "input" to CARBITS is the "Demographic Scenario." The demographic microsimulation used in CARBITS is treated as part of the background baseline calculations, and is not subject to modification by users. This is denoted by the dotted lines in Figure 1.

Table 2.1 CARBITS Body Type and Size Classes

Type	Size
1. Car	Mini
2. Car	Subcompact
3. Car	Compact
4. Car	Intermediate
5. Car	Large
6. Car	Luxury
7. Car	Sports (or, "Sports car")
8. Pickup	Compact
9. Pickup	Standard
10. Van	Compact (or, "Minivan")
11. Van	Standard
12. Sport utility vehicle	Small
13. Sport utility vehicle	Large
14. Sport utility vehicle	Mini

Table 2.2 Vehicle Attributes

Attribute	Measurement Units
1. Body-Type-Size Code	Integer, 1 to 14* (see Table 2.1)
2. Model Year	Integer (1976 to 2010)
3. Purchase Price (New)	Dollars
4. Fuel Economy	Miles per gallon
5. Acceleration Time (0 to 30 MPH)	Seconds
6. Top Speed	MPH
7. Number of Models	
8. Emissions Index	Fraction from 0 to 1. 1 = 1994 gasoline vehicle.
9. Refueling range	Miles (On a full tank.)
10. Market Availability	1 = Vehicle is available, 0 = Not available.

Table 2.3 Excerpt from Vehicle Market Scenario File

```
BTSIZE,VINTAGE,NEWPRICE,FUELECON,ACCEL,TOPSPEED,NUMMODS,EMISS,RANGE,MKTAVAIL
1,1976,6531,28.44,4.96,112,38,1,300,1
2,1976,10793,27.55,4.78,116,17,1,300,1
3,1976,8335,20.77,5.04,120,22,1,300,1
4,1976,8997,21.45,4.86,115,32,1,300,1
5,1976,12722,18.39,4.88,109,17,1,300,1
6,1976,29316,17.29,4.46,141,24,1,300,1
7,1976,10276,20.31,4.37,131,17,1,300,1
8,1976,11586,22.47,5.24,103,7,1,300,1
9,1976,7807,23.16,5.14,101,5,1,300,1
10,1976,16014,19.00,5.83,106,1,1,300,1
11,1976,12092,17.68,5.72,101,5,1,300,1
12,1976,18373,16.00,5.60,100,2,1,300,1
13,1976,15729,13.40,5.33,104,9,1,300,1
14,1976,12345,19.13,5.12,100,3,1,300,1
   .......
1,2015,13875,35.05,4.00,112,18,1,400,1
2,2015,15420,35.00,3.80,116,26,1,400,1
3,2015,15846,31.41,3.68,120,22,1,400,1
4,2015,20540,27.44,3.34,115,28,1,400,1
5,2015,23571,24.72,3.01,109,7,1,400,1
6,2015,44518,24.37,2.58,141,64,1,400,1
7,2015,20691,24.74,2.68,131,15,1,400,1
8,2015,13629,27.59,4.09,103,17,1,400,1
9,2015,18492,20.09,3.68,101,8,1,400,1
10,2015,24516,22.24,3.55,106,17,1,400,1
11,2015,22206,17.24,3.94,101,15,1,400,1
12,2015,26716,21.17,3.57,100,11,1,400,1
13,2015,34493,16.92,3.59,104,7,1,400,1
14,2015,18148,26.65,3.78,100,3,1,400,1
   .......
```

2.2 Base Case Scenario Inputs

To provide more detail on what the current baseline scenario looks like, this section contains graphical summaries the key attributes from the baseline Vehicle Market Scenario file.[4] Smoothed historical averages for the 14 vehicle classes are used for vehicles manufactured during the period 1976 to 2003. Beginning in 2004, projections are used to establish a baseline for policy analysis. Figures 2.1 and 2.2 give average price figures for new light duty auto and light duty truck classes, respectively. Figures 2.3 and 2.4 summarize the performance attribute (acceleration time for 0-30 mph, in seconds) for the light duty autos and trucks, respectively. Figures 2.5 and 2.6 give fuel economy (miles per gallon), for light-duty autos and trucks, respectively. These figures illustrate the nature of historical technological trends (e.g., improvements in performance and variations in fuel economy), and how they are manifested across the various size classes appearing in the market place. Figures for the period 2004-2020 are projections based on CARB staff judgment, and establish the baseline for policy analysis.

Figure 2.1

[4] Dr. Bill Dean of the California Air Resources Board provided these for inclusion in this documentation.

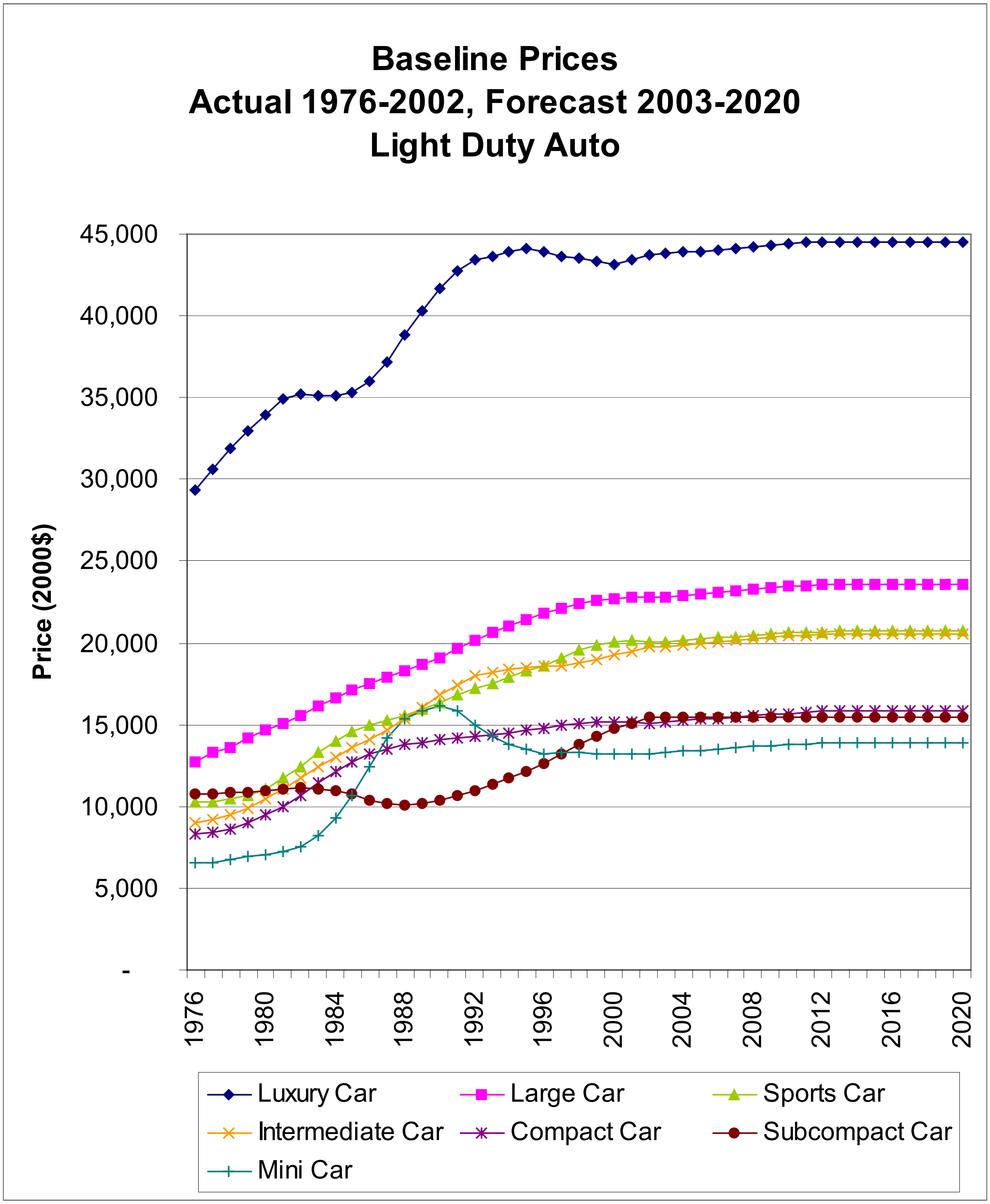

Baseline Prices
Actual 1976-2002, Forecast 2003-2020
Light Duty Auto
Price (2000$)
45,000
40,000
35,000
30,000
25,000
20,000
15,000
10,000
5,000
-
1976
1980
1984
1988
1992
1996
2000
2004
2008
2012
2016
2020
Luxury Car
Large Car
Sports Car
Intermediate Car
Compact Car
Subcompact Car
Mini Car

Figure 2.2

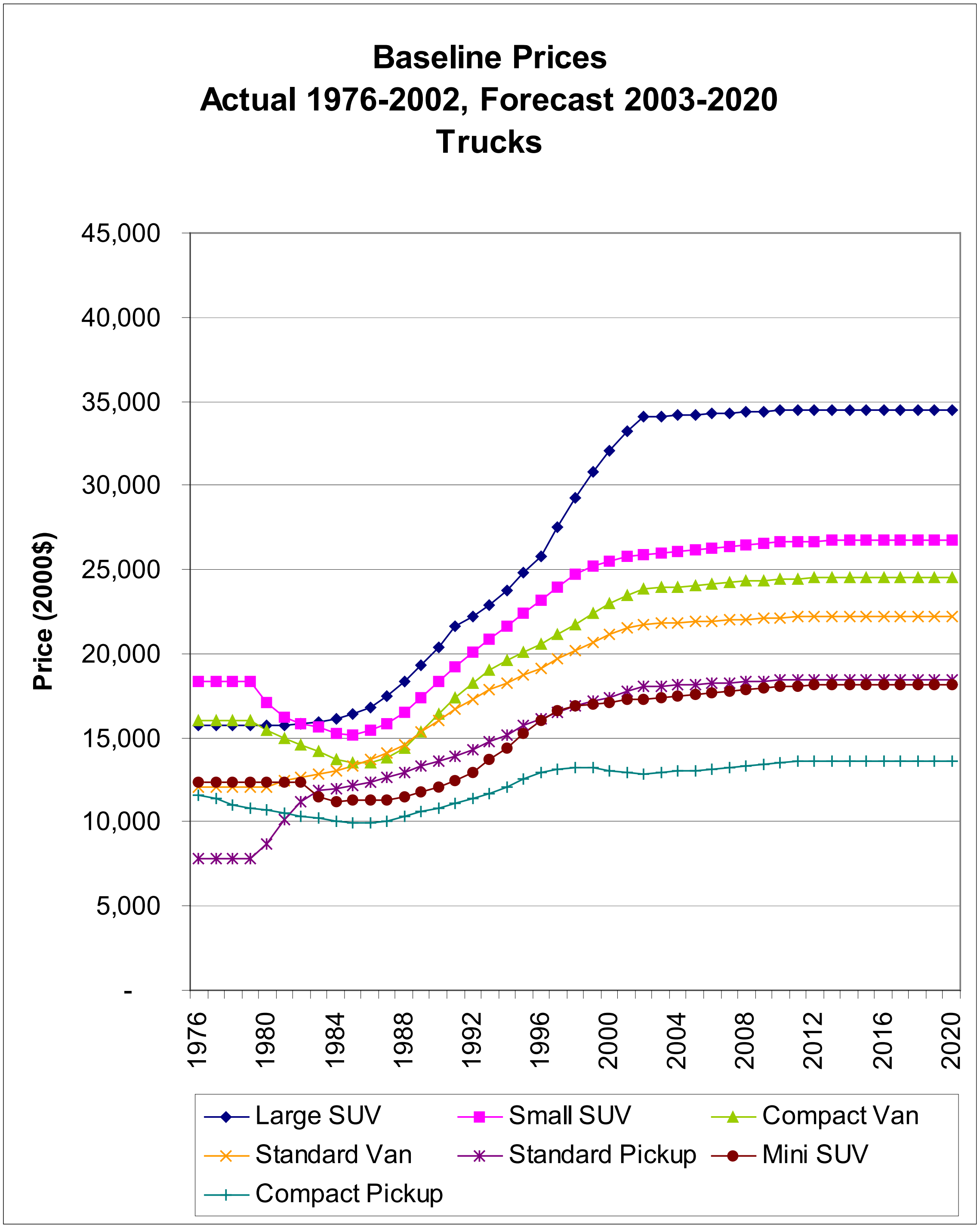

Baseline Prices
Actual 1976-2002, Forecast 2003-2020
Trucks
Price (2000$)
45,000
40,000
35,000
30,000
25,000
20,000
15,000
10,000
5,000
-
1976
1980
1984
1988
1992
1996
2000
2004
2008
2012
2016
2020
Large SUV
Small SUV
Compact Van
Standard Van
Standard Pickup
Mini SUV
Compact Pickup

Figure 2.3

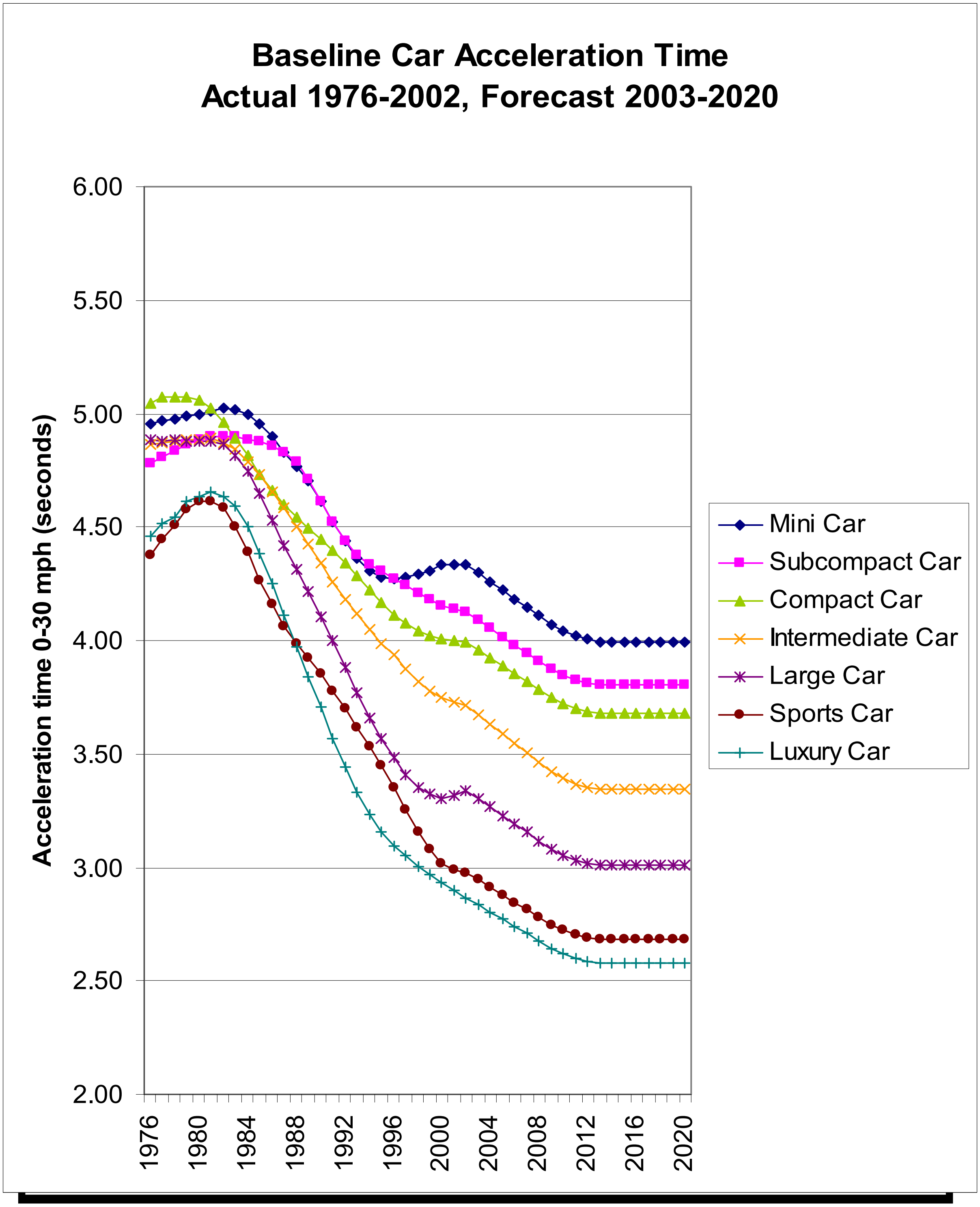

Baseline Car Acceleration Time
Actual 1976-2002, Forecast 2003-2020
Acceleration time 0-30 mph (seconds)
6.00
5.50
5.00
4.50
4.00
3.50
3.00
2.50
2.00
1976
1980
1984
1988
1992
1996
2000
2004
2008
2012
2016
2020
Mini Car
Subcompact Car
Compact Car
Intermediate Car
Large Car
Sports Car
Luxury Car

Figure 2.4

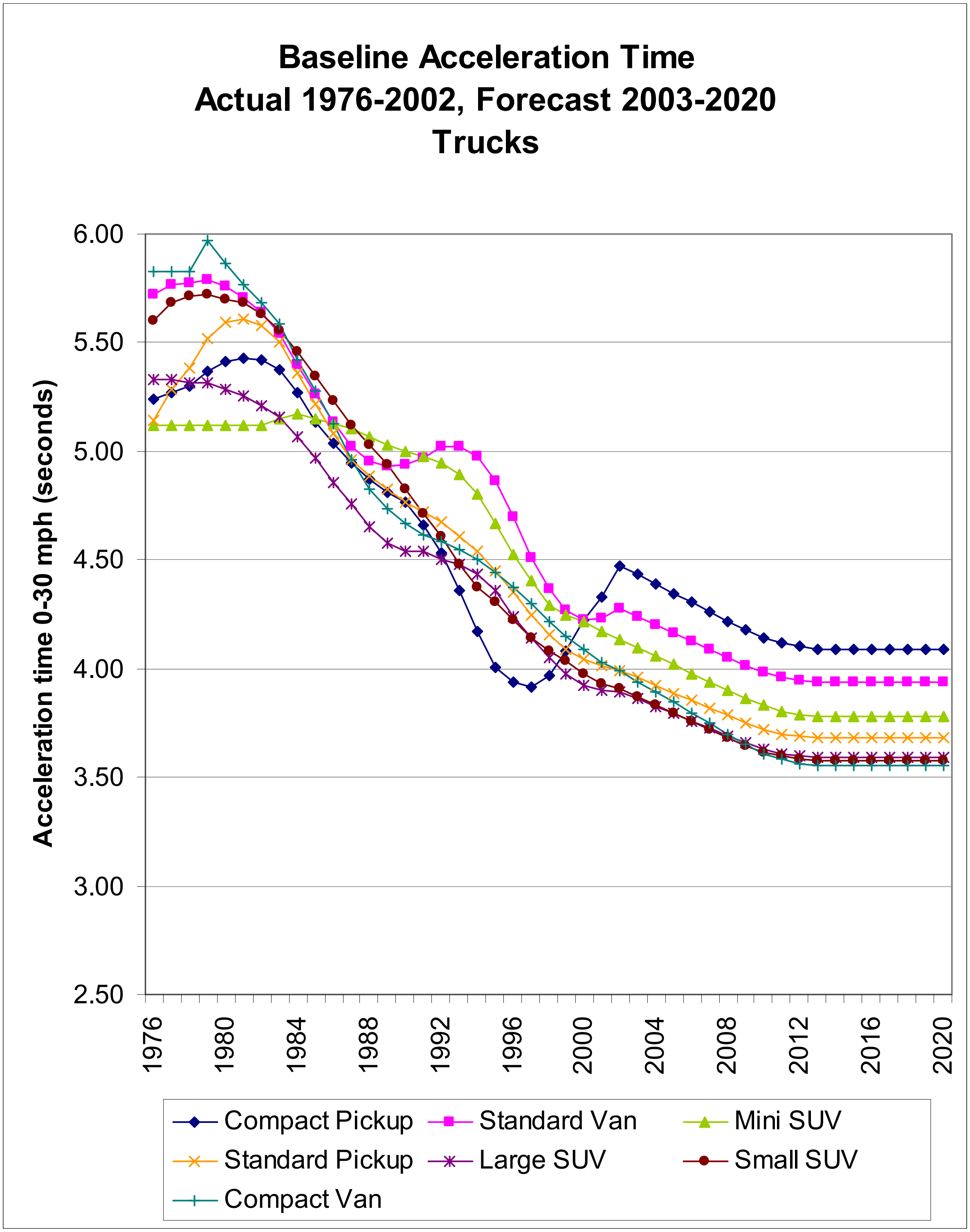

Baseline Acceleration Time
Actual 1976-2002, Forecast 2003-2020
Trucks
Acceleration time 0-30 mph (seconds)
6.00
5.50
5.00
4.50
4.00
3.50
3.00
2.50
1976
1980
1984
1988
1992
1996
2000
2004
2008
2012
2016
2020
Compact Pickup
Standard Van
Mini SUV
Standard Pickup
Large SUV
Small SUV
Compact Van

Figure 2.5

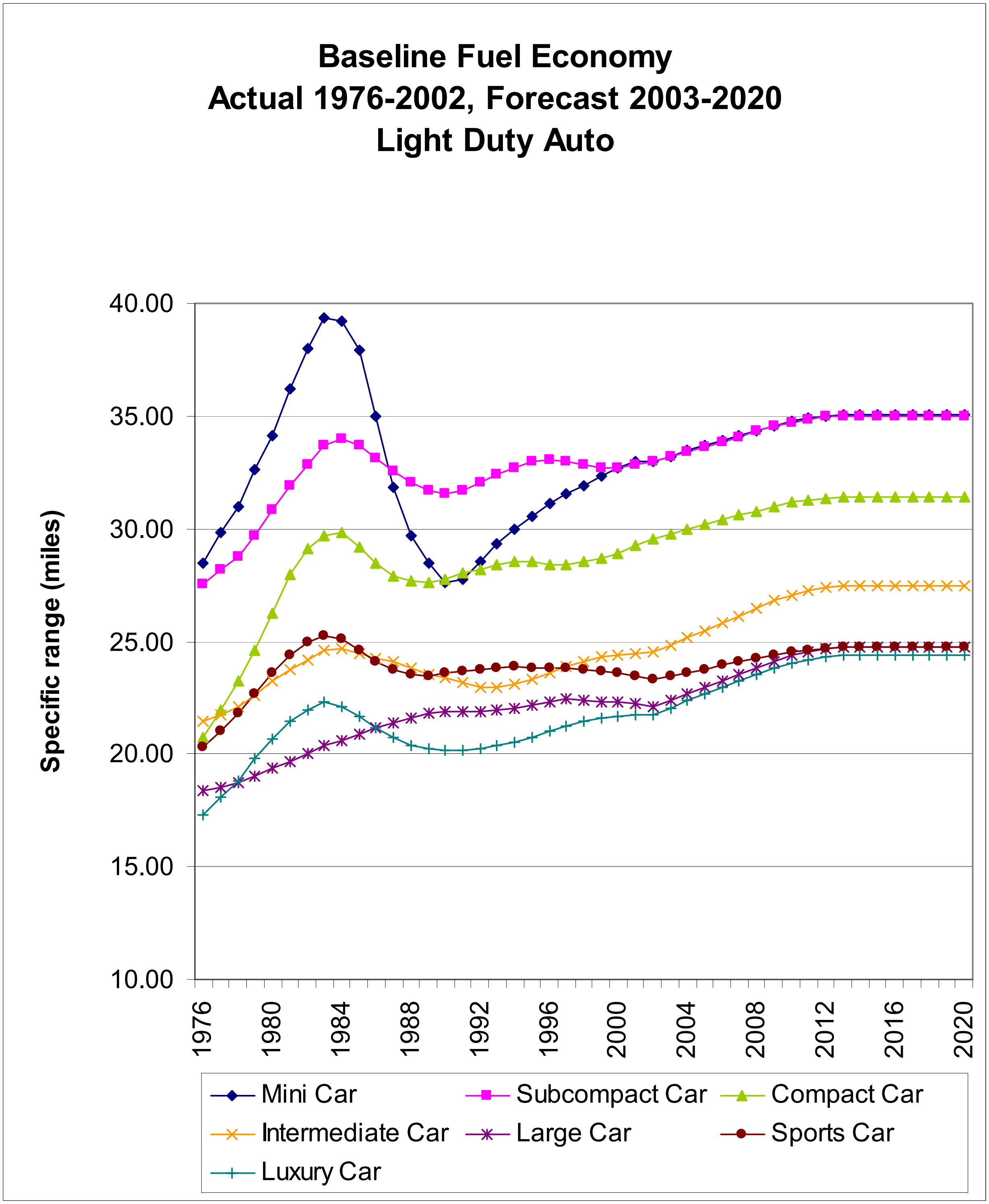
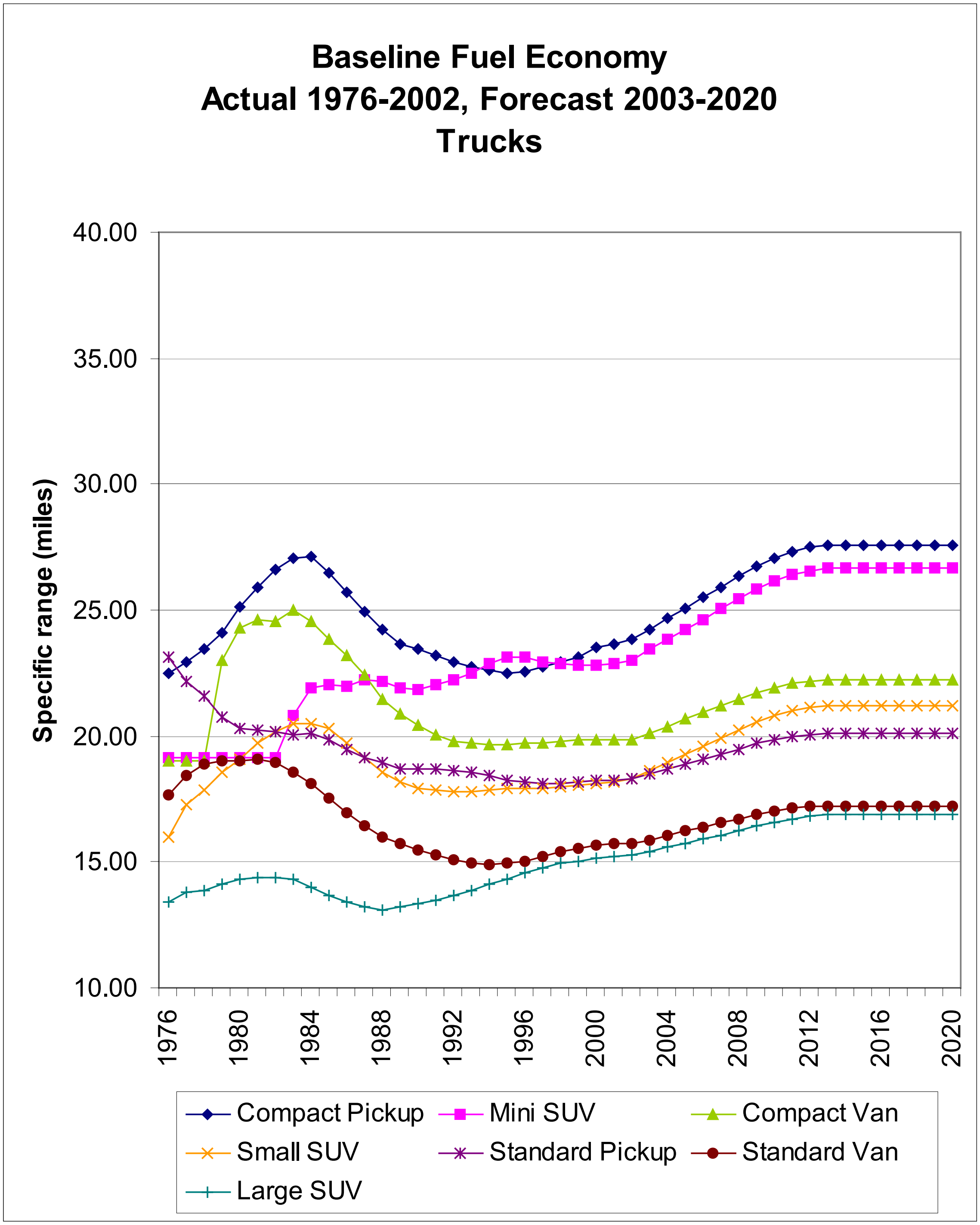

Baseline Fuel Economy
Actual 1976-2002, Forecast 2003-2020
Light Duty Auto
Specific range (miles)
40.00
35.00
30.00
25.00
20.00
15.00
10.00
1976
1980
1984
1988
1992
1996
2000
2004
2008
2012
2016
2020
Mini Car
Subcompact Car
Compact Car
Intermediate Car
Large Car
Sports Car
Luxury Car

Figure 2.6


Baseline Fuel Economy
Actual 1976-2002, Forecast 2003-2020
Trucks
Specific range (miles)
40.00
35.00
30.00
25.00
20.00
15.00
10.00
1976
1980
1984
1988
1992
1996
2000
2004
2008
2012
2016
2020
Compact Pickup
Mini SUV
Compact Van
Small SUV
Standard Pickup
Standard Van
Large SUV

3. CARBITS Outputs

Annual aggregated results from a CARBITS microsimulation run are computed and written to four different output files using the formats described in this section.

3.1 CARBITS Output Formats

One practical modeling issue is that CARBITS simulates the vehicle market using detailed market-based class definitions (see Section 2), whereas policy analysis requirements of CARB frequently require linkages to the EMFAC model, which uses a vehicle classification scheme that is more oriented toward differences between vehicle technologies and their implications for emissions production. Specifically, EMFAC uses the class definitions in Table 3.1.

Table 3.1 EMFAC2000 Vehicle Classes

Class	Code	Description	Weight (GVW, lbs.)
1	PC	Passenger cars	ALL
2	T1	Light-duty trucks	0 - 3,750
3	T2	Light-duty trucks	3,751 - 5,750
4	T3	Medium-duty trucks	5,751 - 8,500
5	T4	Light-heavy duty trucks	8,501 - 10,000
6	T5	Light-heavy duty trucks	10,001 - 14,000
7	T6	Medium-heavy duty trucks	14,001 – 33,000
8	T7	Heavy-heavy duty trucks	33,001 – 60,000
9	T8	Line-haul trucks	60,000 +
10	UB	Urban buses	ALL
11	MC	Motorcycles	ALL
12	SB	School buses	ALL
13	MH	Motor homes	ALL

For our purposes, the personal vehicle market is considered to consist of vehicles in EMFAC Classes 1 through 4 (although there may be a very small number of vehicles that exceed 8,500 lbs. GVW). CARBITS uses an internal weighting scheme (provided by CARB staff) to compute estimates for these classes. Aggregated results for CARBITS-based classes are reported using four market-based (“BT4”) categories: Cars, Trucks, Vans, and SUVs.

CARBITS produces four standardized output files that report counts of “vehicles on the road.” The formats are determined by the vehicle classification scheme (EMFAC or CARBITS) used, and by the level of detail on vintage/age distributions. One vintage format type aggregates all vintages together, and the other uses 20 age groups. In the first vintage-format type, there is one row of results for each forecast year, and five columns. See Table 3.2 for an example. For an example of the second vintage-format type, see Table 3.3.

Table 3.2 CARBITS Output
[Four CARBITS Classes, Annual Counts of Vehicles on the Road]

FCYear	AllVeh	Cars	Trucks	Vans	SUVs
2004	23039374	15390098	3385432	2455664	1808179
2005	23731740	15783068	3507329	2580425	1860918
2006	24359200	16150641	3596104	2681942	1930513
2007	25154870	16653900	3683631	2808588	2008755
2008	26047296	17251932	3818199	2945990	2031173
2009	26884112	17756372	3932128	3105164	2090449
2010	27642724	18203548	4075275	3225496	2138403
2011	28297172	18621700	4206884	3304601	2163990
2012	29125002	19199146	4285089	3409314	2231454
2013	29761244	19684490	4347592	3448613	2280546
2014	30679916	20266228	4561024	3528705	2323960
2015	31793626	20960806	4702259	3683397	2447164

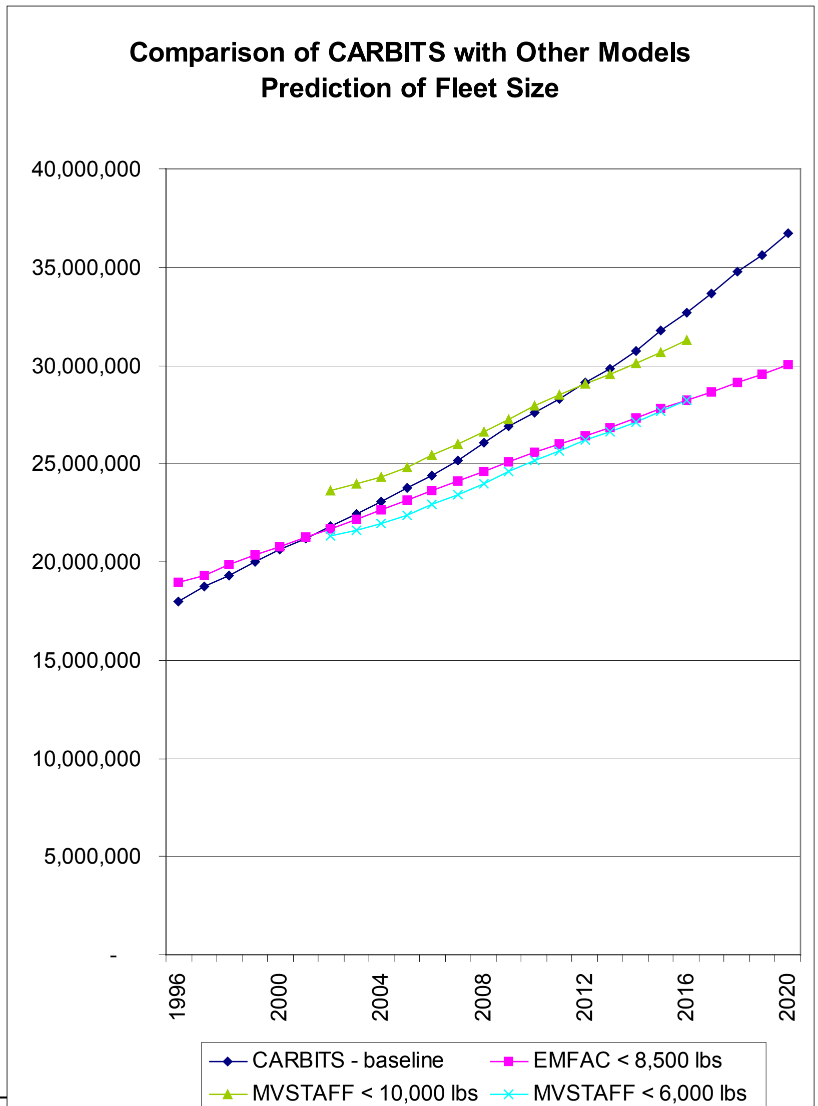
Table 3.3 CARBITS Output [Four EMFAC Classes, 20 Age Groups (excerpt for 2005)]

FCYear	AgeGroup	Decript	All	Cars	LDT1	LDT2	MDV
2005	0	New	1556545	1050636	239948	194537	71424
2005	1	1 yr old	1553604	1022105	263532	200468	67499
2005	2	2 yrs old	1674123	1103494	285943	208816	75869
2005	3	3 yrs old	1610459	1108016	236062	190579	75802
2005	4	4 yrs old	1471974	969189	258970	180336	63480
2005	5	5 yrs old	1362158	941695	183980	171861	64622
2005	6	6 yrs old	1305967	879218	204353	159887	62509
2005	7	7 yrs old	1204081	795651	172452	171199	64778
2005	8	8 yrs old	1282777	874800	181658	163837	62483
2005	9	9 yrs old	1144256	721638	178221	174711	69685
2005	10	10 yrs old	1250502	813134	215157	148621	73590
2005	11	11 yrs old	1049107	656518	182611	136936	73041
2005	12	12 yrs old	897564	623556	117716	106760	49531
2005	13	13 yrs old	672144	437514	104183	92264	38182
2005	14	14 yrs old	722676	476900	102135	92622	51019
2005	15	15 yrs old	711710	469094	109913	87704	44999
2005	16	16 yrs old	711341	500913	92435	78588	39405
2005	17	17 yrs old	701479	447475	87640	109741	56623
2005	18	18 yrs old	620727	417072	83700	80955	39000
2005	19	19 yrs old	570627	393900	77851	68418	30457
2005	20	>=20 yrs	1552193	1080551	187974	174423	109244

3.2 Base Case Results

Using the output obtained from four files described in the previous section, it is possible to produce a variety of graphs and statistics for the base case scenario that might be of interest to policy makers. The highest level of aggregation is the total number of vehicles on the road in California (total "fleet size"). For a comparison of CARBITS results to results from some other California model projections (MVSTAFF, and EMFAC), see Figure 3.1. Figure 3.1 shows that CARBITS tends to predict higher numbers of vehicles than EMFAC.[5] CARBITS projections are most consistent with MVSTAFF projections (for vehicles with GVW < 10,000) up through 2016.

Figure 3.1



[5] EMFAC takes as its starting point vehicle population growth trends obtained from analysis of DMV data in the period around the year 2000. Fleet size projections are then adjusted via a complex process that involves VMT projections obtained from various local planning sources, and per-vehicle VMT assumptions.

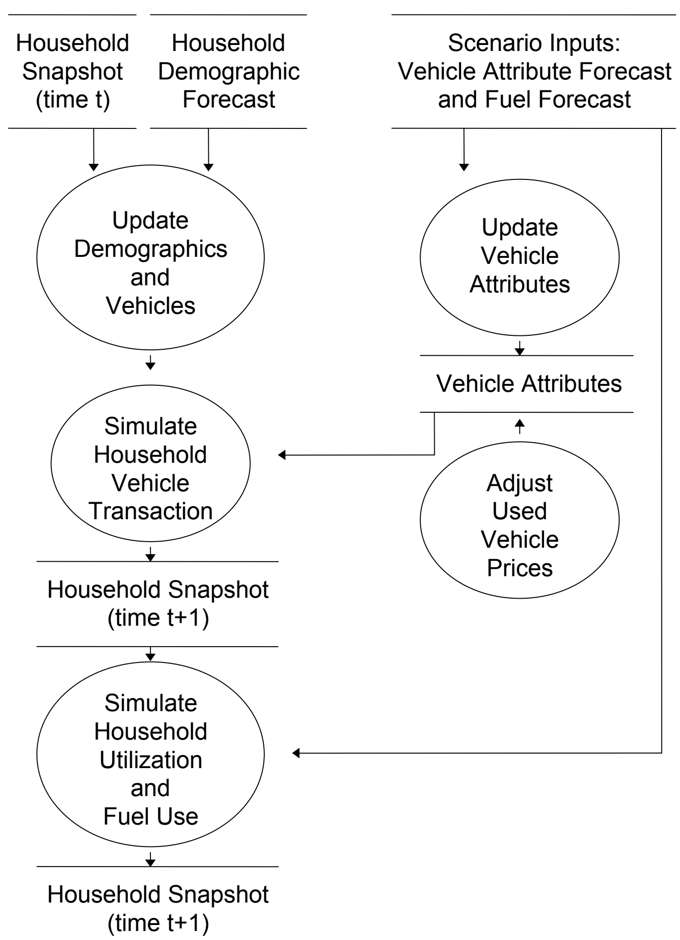
Appendix. Household Data, Vehicle Transactions, and Models

The vehicle transactions model used by CARBITS to simulate household-level vehicle transactions behavior is an adapted version of a model developed by Hongyen Sheng in her PhD thesis (Sheng 1999). Because the full background and details of the behavioral model require a thesis-length treatment, reproducing the material in its entirety is beyond the scope of this document. Moreover, embedding a behavioral model within a microsimulation system raises additional issues. This appendix provides a summary of these key issues and how they are addressed by CARBITS.

A.1 Background

As described in the introduction, CARBITS simulates vehicle transaction choices at the individual household level. Figure A.1 illustrates the overall microsimulation approach, where the household behavioral model ("Simulate Household Vehicle Transaction") is only one component.

Figure A.1. CARBITS Microsimulation Structure



In CARBITS, changes in household demographics are simulated at six-month time intervals. Because simulating these changes is very computer intensive, and because demographic changes are not considered to be a function of household vehicle transaction histories, CARBITS uses a large database of household snapshot files that have been separately generated using a demographic microsimulation program. The demographic database is therefore treated as a "black box" in CARBITS, and represents an immutable part of the baseline scenario for future vehicle markets in California.

This background discussion has been provided to highlight the complexities and issues associated with modeling vehicle markets that might not typically occur to model users (or even possibly to many choice modeling researchers). Specifically, in most cases researchers are focused exclusively on vehicle purchase and/or transaction decisions *conditional* on a *fixed set of demographic inputs*. However, in the real world of data collection it is difficult and costly to obtain precise, detailed information related to the *movement of vehicles* into and/or out of the household. A complicating issue is that not all vehicle movements are due to buying and selling behavior. Some vehicle movements are linked to demographic transitions that are occurring *simultaneously* (e.g., a 21-year old living at home leaves the household and takes a vehicle with her).

Most databases capture cross-sectional information on (i) *current* household demographics, and (ii) *current* vehicle holdings. Even very good databases, e.g., the National Personal Transportation Survey (NPTS) will ask for information on *when* each vehicle was *acquired* (note the terminology), and whether or not it was new or used when *purchased* (which may or may not coincide with the "acquisition"). Vehicles can enter a household through various means (other than through a direct purchase). Households are generally *not* asked about whether the vehicle was *added* to an existing fleet, whether it was purchased as a *replacement* vehicle, and, if so, what vehicle was being replaced. Finally, vehicles that have recently *exited* the household (and *why*) are not usually tracked.

The development of CARBITS has attempted to address as many of these issues as possible. The data used to *estimate* the original behavioral model were obtained as part of a three-wave panel study of California households that specifically collected as much information as possible on actual vehicle movements/transactions. Another household database that plays a major role in CARBITS is the 1995 NPTS survey. This database is attractive because of its large sample size, as well as the quality of the data collection.

To conclude this background section, consider Figure A.2, which depicts an "ideal" version of a vehicle transaction model like the one used in CARBITS. This provides necessary context and background for later discussion of the range of practical issues associated with actually *developing* such a model. Although a variety of model forms could be suggested based on theoretical considerations, the key practical constraint will be data availability. The next section discusses data issues to provide further context for the section describing the CARBITS transactions model.

Figure A.2. Idealized Transaction Choice Model

1. As an example, consider a two-vehicle household.

2. Only *one* vehicle transaction choice is assumed to occur during a time interval (including the choice of "doing nothing," or, "no transaction").

3. Choices during the time interval are conditional on the household's demographics at the beginning of the time interval, as well as the current vehicle holdings (and their attributes).

4. The available choice options* are:

O1. Do nothing.
O2. Add another vehicle to the current fleet by making a purchase.
O3. Replace a current vehicle.
  O3.1 Sell vehicle 1, and purchase a replacement.
  O3.2 Sell vehicle 2, and purchase a replacement.
O4. Sell a current vehicle (with no replacement)
  O4.1 Sell vehicle 1.
  O4.2 Sell vehicle 2.

*Appropriate modifications are made to the choice set depending on how many vehicles the household currently holds.

A.2 Household Data and Vehicle Transactions

Before considering data requirements for estimating a disaggregate (household-level) transaction choice model, we present some aggregate statistics from two different data sources that will inform the later discussion. As previously discussed, the two household data sets that have been used for CARBITS development are (1) the University of California 1993-1997 Panel Survey of California Households, and (2) the 1995 National Personal Transportation Survey.

A.2.1 Panel Survey of California Households

The survey consisted of three waves during the period 1993-1997. Households were contacted at approximately 15-month intervals. A combination of revealed preference (RP) and stated preference (SP) data from Waves 1 and 2 were used to estimate the vehicle transactions model used in CARBITS.

Wave 1 was carried out in June and July of 1993. The sample was generated via an initial computer-aided telephone interview ("CATI-1") using pure random digit dialing of 7,387 households, geographically stratified to cover 79 (urban) public utility district areas in California (excluding San Diego), effectively targeting 75% of the state population. The CATI-1 interview collected information on household demographics and vehicle inventories, commuting patterns, and intentions about the next vehicle transaction. Each household received a customized mail-out survey instrument (using CATI-1 information) that included two experimentally designed discrete choice stated preference (SP) tasks on future vehicle transactions. Responses to the mail-out were successfully retrieved via a follow-up telephone interview ("CATI-2") from 4,747 households (66% of the initial CATI-1 sample).

Wave 2 was implemented through attempted re-contact of the original Wave 1 CATI-1 ("W1C1") sample during August through October of 1994. A total of 2,857 households participated in the W2C1 interview. Of these, 2,243 had participated in W1C2, and 614 had participated in W1C1 only. The W2C1 interview collected information on movements of vehicles into and/or out of the household that occurred since the time of the W1C1 interview, and is the source of the RP data used for estimating the CARBITS transactions choice model. Note that one potential source of bias in these data is the effect of attrition from the panel. The non-attrition households are likely to have different characteristics from the attrition households.

A.2.2 1995 National Personal Transportation Survey

Agencies from the U.S. Department of Transportation have periodically sponsored large household surveys. Our work has drawn extensively from the 1995 National Personal Transportation Survey (NPTS). Background details on this survey are beyond the scope of this report (for a web-based reference, see http://npts.ornl.gov/npts/1995/doc/index.shtml). CARBITS takes advantage of the availability of NPTS data from 40,022 households in national sample. In this sample 38,690 households hold one or more vehicles, and data are available for 65,575 vehicles. The survey has data for only 2,086 households from California, so finding a way to make use of the larger national sample was an attractive option. The current version of CARBITS uses the sample of 40,022 as the base case household database. Weights have been constructed that, when applied, cause the sample "look like" California on key demographic variables. This database is used as the starting point for the demographic microsimulation described in the introduction. The key reference for the demographic microsimulation model is the PhD dissertation of Camilla Kazimi (1995).

A.2.3 Aggregate-level Summaries of Vehicle Movements

To develop some understanding of vehicle movements, we first consider some aggregate level statistics from the two databases (which were collected in similar but not identical time periods). In both data sets, survey data were collected on "vehicles acquired by the household" during a time interval just prior to the survey interview date. In the case of the 1995 NPTS, households were asked to identify which of their current vehicles were *acquired* during the previous twelve months. In addition, they were asked for the year and month of acquisition, and whether the vehicle was purchased new or used. In W2C1 of the California survey, households were asked to identify all vehicles acquired since the previous W1C1 interview (including those vehicles that may have subsequently exited the household prior to W2C1).

Table A.1 gives a comparison of vehicle acquisition distribution statistics for three different cases. The UC statistics are un-weighted raw statistics due to the unavailability of an appropriate set of weights. The NPTS California household results use the internal NPTS weights, and the NPTS National sample is weighted using the weights discussed previously. [However, we note that there are only minor differences between the weighted and un-weighted versions of these statistics (not shown here).]

Table A.1 Vehicle Acquisition Statistics

Entering Vehicles	NPTS (Cal HH)	NPTS (Wtd Nat)	UC Cal Survey
0	72.8	66.5	63.0
1	23.6	28.8	29.8
2	3.4	4.5	6.2
3	0.2	0.3	0.8
4	0.0	0.0	0.1
Exp Num Entering:	0.31	0.39	0.45
Exp Num per Month	0.026	0.032	0.038

The statistics from the three sources tell a similar story, and the differences have reasonably simple explanations. These figures indicate that in any 12–to-15 month period 27 to 37% of households might acquire a vehicle. These figures are perhaps higher than one might expect, but recall that these vehicles include vehicles that entered the household for any conceivable reason, not just traditional purchase decisions (see the previous discussion).

The UC survey figures are a bit higher than the NPTS figures, almost certainly because the time period is three months longer. When adjusted on a per-month basis, the UC survey figures are still slightly higher, probably because the sample is un-weighted. The UC survey sample is slightly skewed toward higher income households with more vehicles. Another possible factor is that the UC survey collected data on all vehicles that entered (even if they subsequently exited), whereas the NPTS data are limited to vehicles actually held at the time of the survey. Another noteworthy observation is: There are a small (but significant) number of households (roughly 5%) that acquire more than one vehicle during an annual period. This fact should be taken into consideration when deciding how to perform the microsimulation. This effect would need to be taken into account if the microsimulation time period is set to one year; alternatively, a shorter time period (e.g., six months) might be an option.

An important aspect of Table A.1 is that it was constructed for vehicle *acquisitions* to allow a direct comparison of the NPTS and UC datasets. As noted previously, these statistics are not necessarily equivalent to vehicle replacement and addition transactions. The UC dataset has more detail in this regard, and some additional statistics will be relevant when considering development of a transaction choice model. A rudimentary data set was constructed from the W2C1 data to explore additional details on vehicle movement. Of the 2857 households in W2C1, 1284 (45%) had some type of vehicle movement into and/or out of the household. Table A.1 identifies 37% of households as acquiring one or more vehicles, so the additional 8% would presumably involve vehicles exiting the household.

The data set identifies 1891 "events" that involve vehicle movement, where these have been assigned to one of three "crude" (preliminary) types: Replace, Add, or Delete. These assignments are based on respondent's answers to questions regarding the basic nature of the vehicle movement, and avoid the premature use of more detailed terms such as "trade," "purchase," "sell," "scrap," etc. These data include information about whether vehicle movements are associated with some type of demographic change, versus a situation where vehicles where actually purchased and/or sold. Table A.2 gives a cross-tabulation of the various categories.

Table A.2. Distribution of Vehicle Movement Events in UC Survey Data

		Replace	Add	Delete	Total
Demog-related	Count	21	191	216	428
	Row %	4.9%	44.6%	50.5%	
Non-demog-related	Count	622	460	381	1463
	Row %	42.5%	31.4%	26.0%	
Combined	Count	643	651	597	1891
	Row %	34.0%	34.4%	31.6%	

Table A.2 reveals that, in terms of raw numbers, the movement types for all observations ("combined") are about equally distributed. However, 428 (23%) of the events involve demographic-related factors that do not reflect the usual notion of a "transaction." For example, 216 (36%) of the Delete events correspond to household members leaving and taking a vehicle with them. The remaining 381 Deletions were described as "sold" or "traded" (195), "wrecked" (24), "scrapped" (21), with the remainder unknown. With regard to Additions, 460 (71%) were clearly identified as cases where a vehicle was purchased or leased. However, the remaining 29% involved events such as a new household member entering, etc.

Consider a household that has had multiple vehicle movements during a 12 to 15 month time period, where the vehicle movements are not related to obvious demographic changes (e.g., a person leaving and taking a vehicle). In the case of an "Add" followed by a "Delete" (or vice-versa), it is reasonable to regard these combined events as equivalent to a single "Replace" event. We specifically identified 168 cases where this occurred (although it is possible that there are more, due to censoring of the data, i.e., a matching Add or Delete event could occur after the W2C1 interview). Treating these 168 cases as replacements, there would then be 1295 non-demographic transactions: 790 (61%) replacements, 292 (22.6%) additions, and 213 (16.5%) deletions. These figures give some additional insight beyond the crude acquisition statistics cited earlier.

Another statistic of interest is the decision to purchase new versus used. A related statistic would be the age (based on model year) of the acquired vehicle. There are fundamental problems associated with these measures. The most familiar case is when next year's "new" vehicles are introduced in the summer of the previous calendar year. However, there are evidently many other situations where the calendar year and the model year are different for "new vehicle purchases." According to Greenspan and Cohen (2000), some vehicles are purchased "new" when the model year is as much as four years older than the calendar year. This issue is explored further in the next section.

A.3 Vehicle Transaction Choice Model

This section summarizes portions of Sheng (1999) to provide documentation on the specification and estimation of her original vehicle transaction choice model. Incorporating the model into CARBITS required some modifications (including calibration-based parameter adjustments) that are also described here.

A.3.1 Sheng (1999) Vehicle Transaction Choice Model.

Consider Figure A.2 as the starting point for developing a vehicle transaction choice model. To estimate a model of this complexity, a variety of practical constraints arise that must be addressed in some fashion. The most immediate problem is missing data, e.g., certain survey questions have missing (refused, don't know) answers. Standard estimation approaches can only use observations that contain a complete set of data elements, and households with missing data are dropped. The biggest problem in the UC Survey was missing information regarding the household's vehicles (e.g., model year, make, model), and perhaps necessary details on some transactions (as implied by the discussion in section A.2). In some cases, key demographic data were also missing. Another practical consideration is that some households have many vehicles (4 or more), and the models grow more complex as the number of held vehicles increases—see Figure A.2, and consider how the options increase as a function of the number of held vehicles.

Sheng (1999) estimates a transaction choice model using a combination of revealed and stated preference data, as previously discussed. Briefly, some assumptions and practical choices she made to perform the estimation are:

1. Households with missing data are dropped.
2. For multiple transaction households, only the first transaction during the observation period is used.
3. The number of "delete" observations was judged by Sheng to be too small for practical analysis, so only *replace* and *add* transactions are considered.
4. Households that have three or fewer vehicles after transacting are included in the analysis.
5. The utility function of Sheng's model is constructed so that the same coefficients are assumed for all households, regardless of how many vehicles they hold. (However, there are explanatory variables related to the size of household and number of drivers that capture important differences.)

Under these assumptions, Sheng identifies 665 "transaction households" for revealed preference (RP) analysis. In addition, she includes 1,561 households that did not transact, for a total of 2,226 RP observations. In the UC Survey, respondents were not explicitly asked if incoming vehicles were purchased as "new" or "used." Vehicles are categorized by their model year (vintage), where (depending on the timing of the transaction) 1993 or 1994 model year vehicles are treated as "new." About 35.5% of the 665 purchase-vehicles are classified as "new" under this rule. Another 14% of vehicles are one-year old, so approximately 50% of vehicles purchased are "relatively new." Figure 2 from Sheng (1999) gives the age distribution of the 665 purchased vehicles, and is reproduced below in Figure A.3. Figure 3 of Sheng (1999) gives the body-type distribution of the 665 purchase vehicles, and is reproduced as Figure A.4 below.

Sheng's vehicle market "universe" contains 729 vehicle types (i.e., various combinations of body types and vintages), which would yield extremely large choice sets for all the relevant transaction alternatives. She therefore uses a sampling approach to randomly generate vehicle sets for estimation purposes (a common practice in choice modeling). In her approach she stratifies her sample based on vintage, so that each vehicle set contains 3 new vehicles, 3 one-to-two year old vehicles, 3 three-to-ten year old vehicles, and 3 vehicles greater than ten years old.

3.1.1 Figure A.3. [Figure 2, Sheng (1999)] The vintage distribution of the vehicles purchased by the 665 households

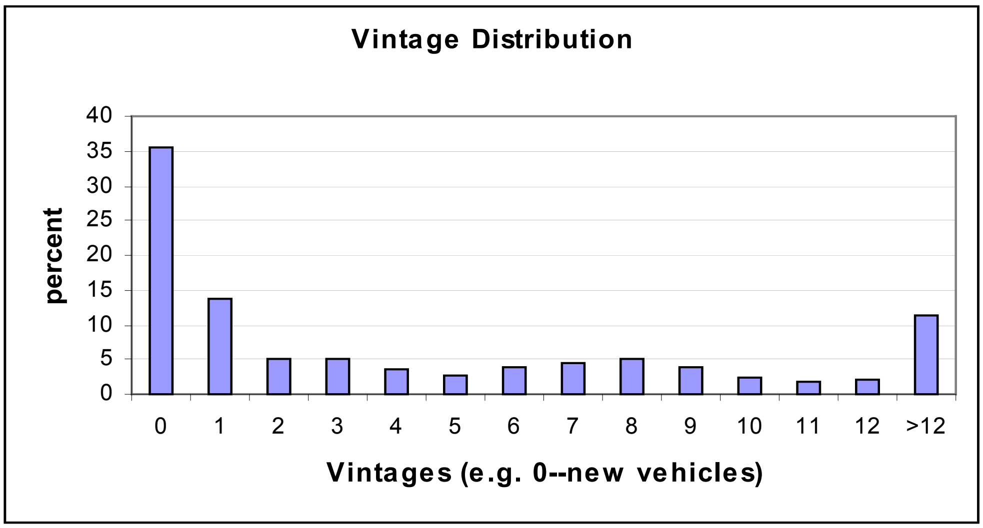
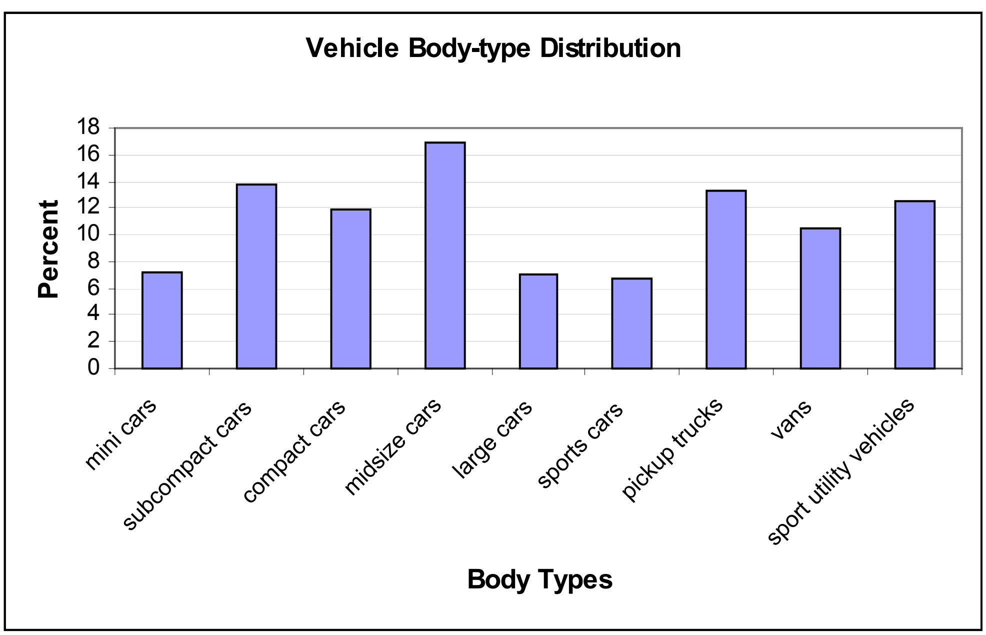


Figure A.4. [Figure 3 of Sheng (1999)]
The body-type distribution of the vehicle purchased by the 665 households



As part of her thesis work, Sheng estimates an “RP-only” multinomial logit model using the 2,226 observations described previously. (We do not include those results here.) The RP-only model compares favorably to other RP-based models in the literature in terms of goodness-of-fit, interpretability of parameter estimates, and asymptotic t-score values.

In the UC study, additional vehicle transaction preference data was available from respondents in the form of a stated preference (SP) choice experiment. Each respondent was given two customized choice tasks. Each SP choice task contained descriptions of six hypothetical vehicles. Respondents were asked to choose their most preferred vehicle. Then, respondents were asked to indicate what they would do if they purchased the most preferred vehicle: would they add the vehicle, or replace a current vehicle? If they indicated “replacement,” they were asked to indicate which of their current vehicles would be replaced. (Some choice tasks included a “delete” option, but these were not considered in Sheng’s analysis.)

Using recently developed approaches in discrete choice modeling, Sheng performed a joint model estimation using the combined RP and SP data sets. This approach allows all the information from each data set to be used to the maximum effect. A full discussion is beyond the scope of this appendix, but some key ideas are summarized.

Wherever possible, model coefficients for common explanatory variables are estimated using data from both two data sets (e.g., coefficients on price, fuel cost, or other generic attributes). Generally, hypothesis tests are performed to ensure that common coefficients are indeed supported by the data, and do not represent a misspecification due to, e.g., biases in the SP data. The key concept here is that potential scale differences between the two data sets must be taken into account. It has been determined in recent studies that perceived differences between RP and SP coefficients that were previously attributed to bias were, in actuality, due to a scaling phenomenon. Once scale differences are taken into account, the null hypothesis that the coefficients are the same in each data set is frequently accepted.

Obviously, if new attributes exist in the SP experiment that do not exist in today’s vehicle market (e.g., attributes related to new alternative fuel vehicles), then these coefficients are determined exclusively by the SP data. However, the joint estimation ensures that these coefficients are properly scaled relative to the generic coefficients. Alternative-specific constants (ASC’s) are typically modeled separately for the two data sets, where the RP-determined ASC’s are considered to be the appropriate ones for capturing the real-world effects. In this data set, the RP data in particular determine the ASC’s relating to transact versus non-transact (since this choice does not even appear in the SP task), as well as add versus replace.

Sheng's coefficient estimates for a multinomial logit model estimated using these data are reproduced in Table A.3. Many of the coefficients in this model are not currently being used by CARBITS, since CARBITS is not currently intended to be used for analyzing markets containing alternative fuel vehicles of the type targeted by the UC research program. In addition, SP-related alternative specific constants are not used (as discussed previously).

Definitions of the explanatory variables are as follows:

a. Net Capital Cost
For add transactions:
Net Capital Cost = Market Value (MV) of Purchase Vehicle.
For replace transactions:
Net Capital Cost = MV of Purchase Vehicle – MV of Replaced Vehicle
For non-transact option:
Net Capital Cost = 0

Net Capital Cost is measured in $1,000. Our research (e.g., Brownstone, Bunch, and Train 2000) has generally found that there is an "income effect" associated with preferences for this variable. To capture this, Net Capital Cost is divided by the natural-log of household annual income (in $1,000).

b. Average Fuel Cost
This variable is constructed to be the average fuel cost of the household's fleet after the vehicle transaction choice. For the "no transaction" option, it equals the average fuel cost for the existing fleet of held vehicles. The units are cents per mile, computed using vehicle fuel economy and an assumed gasoline price of $1.20/gallon (in 1995 dollars). As for Net Capital Cost, average fuel cost is divided by the natural-log of household annual income (in $1000).

Sheng hypothesized that the preference for Average Fuel Cost could vary according to transaction type. She therefore included interaction terms with the "inertia" dummy variable (associated with the no-transact choice), and the "addition" dummy variable. The estimated coefficients for these two interaction terms are positive, and substantially offset the negative coefficient for the main effect. Sheng interpreted this as evidence that households that are replacing vehicles "pay more attention" to fuel costs than those who are not transacting, or who are adding vehicles. Although this effect may not be surprising in a data set of this type, we have concluded that this constitutes a specification error in the model. The implications of these particular coefficients are counterintuitive under the case of increasing gasoline prices, which would predict that households would be more likely to either hold on to their existing vehicles or add a new vehicle (versus replacing a vehicle). We discuss this further in the next section.

c. Average Acceleration Time

Acceleration time is measured as the time to reach 30 mile/hour from a complete stop (in seconds). As with Average Fuel Cost, the Average Acceleration Time is the fleet average after the transaction choice.

d. Average Top Speed
Top speed is miles/hour (in 100's). Average Top Speed is the fleet average after the transaction choice.

Note: The use of attribute averages in the previous variables was adopted to allow a single model to be estimated for all households, rather than estimate separate models for households with different numbers of held vehicles.

e. Range of the Purchase Vehicle
Range = the distance a vehicle can travel between refueling/recharging (in hundreds of miles).

f. Maximum Range of Held Vehicles
Measured in hundreds of miles.

g. Tailpipe Emissions of Purchase Vehicle
This is defined on a scale where 1 = 1994 new gasoline vehicles. This variable was manipulated in the SP experiment to capture preferences for alternative fuel vehicles with lower emissions. In the RP data, an attempt was made to estimate this value for historical vehicles. Unfortunately, in RP data this variable is highly correlated with other variables such as vintage and vehicle body type. The estimated RP coefficient is positive and significant, whereas the estimated SP coefficient is negative (as expected) and marginally significant. We chose to use the SP coefficient in CARBITS.

h. Vehicle Body Type Dummy Variables
Sheng elected to use a limited set of body type dummy variables in her specification, using the following categories: small cars (including mini cars, subcompact cars, and compact cars), large cars (including midsize and large size cars), sport cars, trucks (including compact pickups and standard pickups), vans (including compact and standard vans), mini sport utility vehicles and sport utility vehicles (including compact and standard sport utility vehicles). The midsize/large car category is used as the base for purposes of dummy variable specification.

i. Import/Domestic Vehicles
In Sheng's model development, she included an attribute for import versus domestic. This was implemented via an "import" ("foreign") dummy variable. CARBITS does not include this distinction.

j. Luxury Vehicles

In Sheng's model development, vehicles were classified as either "high price tier" vehicles ("luxury") or "low price tier" vehicles. In CARBITS, there is a single luxury car class.

k. Vehicle Vintage Variables.
Vehicle Vintage = Calendar year – Vehicle model year (as discussed previously). Sheng's specification includes a dummy variable for "new" (vintage = 0), and for one-year-old vehicles. In addition, the natural log of vintage is used to capture the depreciating utility of vehicles due to age.

l. Number of Vehicles in Class
Sheng follows other approaches in the literature that use vehicle classes (e.g., Train 1986), which include the natural logarithm of the number of makes in the class as an explanatory variable.

m. Transaction-Type-Choice Dummies
Sheng includes and "inertia" dummy variable for the no-transact choice, and an "addition" dummy variable. Replacement transactions are treated as the "base" alternative.

n. Household Demographic Characteristics and Changes
There are several interaction terms that capture the effects of demographics on transaction choices. For example, households with more drivers are more likely to add a vehicle.

o. Household Vehicle Portfolio Effects
In multiple-vehicle households, there are certain combinations of vehicles that might be more likely than others. In a dynamic context, a household could be more likely to replace a vehicle with a similar type of vehicle to maintain a favored vehicle mix. This is reflected in various variables in Sheng's model. Two particular effects are: the (total) market value of the remaining household vehicle(s) (after transaction choice), and the vintage of the oldest vehicle in the final portfolio. The former represents a form of "wealth" held by the household, and was found to be important in earlier models. The latter reflects the level of disutility associated with the age of the oldest vehicle.

Table A.3. [Adapted from **Table 6 of Sheng (1999)]**
Multiple-Vehicle Household Joint RP/SP Transaction Model Estimation Results

Explanatory Variables	MNL Coeff. (T-STAT)	Used in CARBITS? See note 5 below
Cost Variables (Joint RP/SP)		
net capital cost /ln(household income/$1k) (in $1k)	-0.351 (-9.069)	Yes
average fuel cost/ln(household income/$1k) (in cents/mile)	-0.342 (-4.196)	Yes
average fuel cost * non-transaction dummy	0.351 (2.745)	No, spec error
average fuel cost * addition dummy	0.285 (2.085)	No, spec error
Vehicle Performance Attributes		
average acceleration time (in seconds) (joint RP/SP)	-0.088 (-2.316)	Yes
average top speed (in hundreds of miles/hour) (joint RP/SP)	0.556 (2.036)	Yes
range of the purchasing vehicle (in hundreds of miles) (joint RP/SP)	0.471 (7.417)	Yes
max range of held vehicle(s) (in hundreds of miles) for RP	2.954 (3.273)	Yes
maxim range of held vehicle(s) (in hundreds of miles) for SP	0.260 (1.011)	No, used RP
squared maximum range for the RP data	-0.393 (-3.751)	Yes
squared maximum range for the SP data	-0.043 (-1.011)	No, used RP
Vehicle Pollution Measurement		
tailpipe emission of the purchasing vehicle for the RP data	0.302 (3.626)	No, used SP
tailpipe emission of the purchasing vehicle for the SP data	-0.356 (-1.594)	Yes
Purchasing-Vehicle-Body-Type Dummies		
small cars for the RP data	-0.259 (-2.084)	Yes
small cars for the SP data	-0.153 (-1.461)	No, used RP
sport cars for the RP data	-0.056 (-0.179)	Yes
sport cars for the SP data	1.177 (1.826)	No, used RP
pickup trucks for the RP data	-0.281 (-1.853)	Yes
pickup trucks for the SP data	-0.966 (-6.130)	No, used RP
vans for the RP data	-1.076 (-2.893)	Yes
vans for the SP data	0.237 (1.332)	No, used RP
sport-utility-vehicles for the RP data	0.591 (2.184)	Yes
sport-utility-vehicles for the SP data	0.874 (1.328)	No, used RP
mini-sport-utility-vehicles for the RP data	-1.430 (-1.871)	Yes
mini-sport-utility-vehicles for the SP data	-1.297 (-1.034)	No, used RP
Other Attributes of the Purchasing Vehicle (RP only)		
natural logarithm of number of makes in the same-size class	0.793 (10.611)	Yes
luxury vehicles	-0.249 (-1.662)	Yes
foreign vehicles	-0.371 (-3.010)	No
new vehicles	1.122 (6.053)	Yes
1-year-old vehicles	0.354 (1.762)	Yes
natural logarithm of vehicle vintage	-0.380 (-3.229)	Yes

Household Portfolio-Choice Variables		
replacing-lower-value-vehicle dummy for the RP data	0.139 (0.906)	Yes
replacing-lower-value-vehicle dummy for the SP data	0.658 (3.148)	No, used RP
replacing-same-body-type-vehicle dummy for the RP data	0.659 (5.383)	Yes
replacing-same-body-type-vehicle dummy for the SP data	1.383 (12.028)	No, used RP
oldest vehicle vintage (RP only)	-0.043 (-4.538)	Yes
market value of the remaining held vehicles (in $1k) (joint RP/SP)	0.111 (7.136)	Yes
from no-car households to one-car households for the RP data	0.199 (1.524)	Yes
from no-car households to one-car households for the SP data	-0.351 (-1.548)	No, used RP
from no-sport-car households to one-sport-car households - RP	-0.439 (-1.306)	Yes
from no-sport-car households to one-sport-car households - SP	-0.078 (-0.112)	No, used RP
from no-van households to one-van households for the RP data	0.931 (2.528)	Yes
from no-van households to one-van households for the SP data	-1.401 (-0.226)	No, used RP
from no-SUV households to one-SUV households for RP data	0.043 (0.159)	Yes
from no-SUV households to one-SUV households for SP data	1.174 (1.661)	No, used RP
all domestic vehicle(s)	0.359 (3.153)	Yes
all imported vehicle(s)	0.479 (4.287)	Yes
Specific Attributes of Alternative Vehicles (SP only)		
electric vehicles	-0.100 (-0.354)	No, gasoline only
electric sport cars	-0.528 (-0.982)	No, gasoline only
electric pickup trucks	-0.346 (-1.056)	No, gasoline only
compressed natural gasoline vehicles	0.587 (3.129)	No, gasoline only
methanol vehicles	0.752 (4.483)	No, gasoline only
electric vehicle * having college education	0.535 (2.723)	No, gasoline only
addition constant * electric vehicles	0.953 (4.520)	No, gasoline only
refueling/recharging station availability	0.637 (3.204)	No, gasoline only
Transaction-Type Dummy Variables		
“inertia” i.e. non-transaction choice (RP only)	7.120 (14.101)	Adjusted
addition constant for the RP data	-0.071 (-0.247)	Adjusted
addition constant for the SP data	0.123 (0.303)	No, used RP
Demographic Characteristics and Changes		
addition*number of vehicles less than or equal to number of drivers (joint RP/SP)	1.808 (13.338)	Yes
addition * households with annual income<=$45k for RP data	-0.131 (-0.836)	Yes
addition * households with annual income<=$45k for SP data	0.304 (1.599)	No, used RP
addition * households with annual income>$90k for RP data	0.569 (2.724)	Yes
addition * households with annual income>$90k for SP data	0.015 (0.040)	No, used RP
addition or replacement* household demographic	0.094 (0.905)	Yes

change(s) (joint RP/SP)		
vans * household size >= 3 (joint RP/SP)	0.906 (5.089)	Yes
sport cars * household size >= 3 for the RP data	0.758 (2.377)	Yes
sport cars * household size >= 3 for the SP data	-1.208 (-1.387)	No, used RP

Notes: 1) the log-likelihood values for the joint multinomial logit model is -7043.851; 2) the number of observations is 99930 and the number of households is 3852; 3) the pseudo R^2 value is 0.423; 4) the "base" vehicle class is "midsize/large" cars and the "base" fuel type is gasoline; 5) "spec error", the interaction variable produces a specification error – "used RP", RP response is considered better than SP response – "used SP", this RP variable is highly correlated with others, so SP response is better – "gasoline only", CARBITS is not dealing with alternative fuel vehicles – "Adjusted", adjusted to compensate for changes in the average utilities associated with dropping interaction terms.

A.3.2 Incorporation of the Transaction Choice Model into CARBITS

Recall that the transaction choice model from the previous section is embedded within the CARBITS microsimulation framework depicted in Figure A.1. This section summarizes various additional actions that were required to incorporate the model into a dynamic microsimulation. A complete understanding of some issues could require an expert-level background, and a full treatment is beyond the scope of this document.

Some initial issues that involve selection of coefficients have previously been discussed in section A.3.1. For those explanatory variables where separate RP-only and SP-only coefficients were estimated, the RP-only values were adopted (the usual practice). The only exception was the emissions-level coefficient, where the SP version was deemed superior. The only key change based on expert judgment was to drop the interaction terms between fuel operating cost and transaction-type choice. The “inertia” and “addition” coefficients were subsequently adjusted to compensate for changes in the average utilities associated with dropping these variables.

The remaining issues fall under the heading of “calibration.” A short review of the standard calibration approaches that are used with multinomial logit (MNL) models provides a useful background discussion. (For a reference, see Train 1986). Most applications of choice models in transportation are based on modeling the choice of vehicle *holdings*. During a particular time period, households are modeled as making the following (simultaneous) decisions: (1) how many vehicles to hold, (2) what portfolio of vehicles to hold. Recall that the choice models are estimated on a relatively small sample of households in order to estimate coefficients for generic explanatory variables such as price, fuel cost, etc. The remaining unobservable factors for the various vehicle types are captured by alternative specific constants, and, in the MNL model, the presence of these constants ensures that the aggregate market shares in the sample are explained exactly. However, because the data come from a small sample of households, these market shares rarely correspond exactly to aggregate market share statistics that might come from a “more accurate” data source based on “census” data (e.g., DMV data) or a data set with a much larger sample size. When such models are placed in a forecasting framework, the alternative specific constants are typically adjusted so that the aggregate market shares from the model are constrained to match “administrative statistics” provided by the user.

Similar adjustments are required for the transaction choice model in CARBITS. However, the calibration requirements are different because CARBITS is simulating transaction choices, not holdings choices. CARBITS requires a different approach. The first adjustment in CARBITS is made to the household weights rather than to the model itself. Specifically, the base case sample of households has a vehicle type distribution that is a function of the demographic weights assigned to the database. The vehicle distribution is similar, but not identical to, distributions that we have looked at from other sources. In CARBITS, we have elected to use the EMFAC distribution as our source of “administrative statistics.” The current version of CARBITS uses a form of iterative proportional fitting (IFP) to adjust household weights to more closely match the following two distributions: (1) the vintage distribution of all vehicles on the road, (2) the vintage distribution of cars (versus light duty trucks) on the road. The former is matched exactly, whereas the latter is matched “closely” but not exactly, due to the complex nature of a dataset containing multiple-vehicle households.

In the original ITS model on which CARBITS is based, vehicle transactions were simulated at six-month time intervals, i.e., using the same time scale as the demographic transitions. In the current version of CARBITS, we have elected to simulate transactions on an annual basis. The key calibration issue for CARBITS is to simulate various transaction *rates* so that they are appropriate for a one-year period. In this regard, the aggregate statistics to be considered include the following: (1) total number of transactions, (2) total new vehicle sales, and (3) total vehicles on the road. A critical area related to item (3) requiring direct intervention is the model’s simulated “scrappage” behavior, i.e., the rate at which various vehicle types leave the system. The unadjusted transaction choice model captures the preferences of the original household sample used for estimation, but does not match these aggregate statistics without some additional adjustments.

The key issue for the transaction choice model is the simulation of scrappage. Recall that the original model did not include “delete” transactions. However, even if it did, this is only part of the story, because vehicle “deletions” represent sales of held vehicles that may or may not correspond to “scrappage.” In CARBITS, the number of scrapped vehicles for any particular vehicle type is given by the net change in vehicles on the road during the period. This is given by:

Vehicles Held (no transaction) + Vehicles Bought – Vehicles Sold.

In CARBITS, vehicles are sold as part of replacement transactions. Vehicles are purchased in both replace and add transactions. To create a reasonable balance between purchases and sales, the major required adjustment was to reduce the relative number of “add” transactions. In addition, the following design feature was added to the simulation: for vehicle types of vintage/age 0-19 years, vehicles could be both purchased and sold, but for vehicles 20 years or older, households could only sell held vehicles, i.e., purchases of vehicles 20+ years old are disallowed.

To make calibration adjustments to CARBITS, transaction statistics associated with the initial simulation year (1996) were computed. Parameters (primarily the dummy variables on “inertia” and “add”) were adjusted so that the overall transaction behavior(s) matched the benchmarks mentioned earlier. EMFAC figures were used to establish benchmarks for scrappage rates as a function of vintage. Benchmarks on overall transactions rates, and sales rates as a function of vintage, were estimated using the NPTS data discussed previously. It is important to note that calibrations were performed using only the first year simulation. It was encouraging to observe that CARBITS forecasts for the next 5-10 years produced figures that were in reasonable agreement with EMFAC figures with no further adjustments required.

For completeness of documentation we describe a few other details of the CARBITS implementation. The CARBITS microsimulation requires annual adjustment of used vehicle prices. One potential approach would be to include an equilibration module and perform price equilibration calculations for each time period. However, this was beyond the scope of our current project. Instead, we employed a straightforward price depreciation scheme based on an analysis of used vehicles that was performed by a graduate student during our previous research project. In future work we would like to add price equilibration to CARBITS.

Another implementation detail is related to demographic-related vehicle movements. The transaction choice model only takes into account vehicle movements due to actual purchases and sales of vehicles. CARBITS includes a separate module that applies certain "vehicle movement rules" when households undergo demographic changes. For example, if a household splits into two separate households due to a divorce, or, if an adult member leaves to create a new household, the vehicle fleet is divided up across the two "new" households.

A.4 References

Greenspan, Alan and Darrel Cohen (1999). "Motor Vehicle Stocks, Scrappage, and Sales," *Review of Economics and Statistics*, 81 (3): 369-383.

Kazimi, Camilla (1995). *A Microsimulation Model for Evaluating the Environmental Impact of Alternative-Fuel Vehicles*. Unpublished PhD dissertation, Department of Economics, University of California, Irvine.

Sheng, Hongyan (1999). *A Dynamic Household Alternative-Fuel Vehicle Demand Model using Stated and Revealed Transaction Information*. Unpublished PhD dissertation, Department of Economics, University of California, Irvine.

Train, Kenneth (1986). *Quantitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand*, The MIT Press, Cambridge.